An Exploration of Human Information Search with the Visual Foraging Task

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要旨

人間の行動には視覚をはじめとする感覚情報の探索が不可欠である。本研究は、人間が特徴や位置に基づいて視覚情報を探すことを視覚情報探索と呼び、これまでの探索の経験と学習による視覚情報探索の変化を、視覚採餌課題を用いて調べたものである。

第1部では、これまでの視覚情報探索に関する研究を紹介し、視覚探索課題を用いて行われてきた研究の動向を説明した。視覚探索課題は、コンピュータの画面に表示される複数の視覚刺激の中から、標的として指定された特定の視覚刺激を見つける課題である。この視覚探索課題中の情報処理過程を説明する理論が複数提案されており、これらに基づいて、新たにコンピュータの画面上ではなく現実世界における視覚情報探索を研究しようとする動きが現れてきた。しかし、これらの理論は情報処理過程における現実世界の表象の中で行われる探索を想定しており、表象内の探索を支える要因が、現実世界の探索をも同様に支えるかどうかは明らかではない。そこで本研究は、視覚情報探索の情報処理過程ではなく機能に注目し、最適採餌理論を利用した視覚情報探索研究の枠組みの構築を目指して、2つの研究を実施した。

最適採餌理論は、動物が餌を探して食べる採餌行動を主に2種類に分類して、単位時間あたりの餌獲得率を最大化する方略を調べるものである。現在採餌を行っている環境から別の環境へ、いつ移動すれば採餌行動全体の餌獲得率を最大化できるかを調べる問題をパッチ離脱問題と呼ぶ。環境に複数種類の餌が存在する場合に、どの餌をどの割合で獲得すれば採餌行動全体の餌獲得率を最大化できるかを調べる問題を最適メニュー問題と呼ぶ。第2部では、動物の採餌場面を模した視覚探索課題である視覚採餌課題を用いて、標的刺激の視覚特徴の学習の阻止が、最適メニュー問題とパッチ離脱問題の意思決定に及ぼす影響を調べた。視覚採餌課題における参加者の課題は、画面に表示される複数の刺

激の中から任意の刺激をマウスでクリックして点数を獲得することであった。画面上にはクリックすると点数が獲得できる得点刺激と、減点される減点刺激があった。1 画面中で何個でも刺激をクリックすることができ、点数を十分獲得したと思ったら、次の新しい画面に移動することができた。実験 1 では、標的刺激の視覚特徴の学習を阻止した群の方が、統制群よりも刺激の選択にかかる反応時間が長かった。実験手続きを改善して実施した実験 2・3 では、阻止群の方が統制群よりも、得点刺激を正しくクリックできる割合が低かった。一方で、次の画面に移動する時間は常に最適よりも遅く、統制群と阻止群の違いはなかった。これらの結果から、視覚特徴の学習の阻止は、視覚採餌課題における最適メニュー問題の意思決定を妨害するが、パッチ離脱問題には影響を与えないことが示唆された。

そこで、最適メニュー問題の意思決定が実際に最適な方略に基づいて行われているか調べるため、第 3 部の研究を実施した。第 2 部の実験と同様の課題を実施した。得点刺激と減点刺激は色で識別できるが、色は重複する 2 つの正規分布によって決定したため、完全に識別することはできないようになっていた。信号検出理論を用いた最適メニューモデルを利用して、この不確実性を最適メニュー問題に取り入れた理論をベイズ統計モデルの形で表現し、最適方略のシミュレーションと実際の方略との比較を行った。また、探索の経験の影響を調べるため、8 画面で構成されるセッションごとに得点刺激の割合 (実験 1) と減点刺激の点数 (実験 2) を変化させた。その結果、どちらの実験でも、参加者は環境の変化にあわせて刺激選択の判断基準を変えたが、経験する順番による影響を受けて、最適方略からは逸脱した。

2 つの研究結果を踏まえて、第 4 部では今後の展望と課題について述べた。視覚探索課題を用いた研究は多いものの、探索する主体と環境との相互作用に着目した研究はまだ盛んであるとは言えない。本研究は最適採餌理論を利用す

ることで、環境の変化に応じて方略を変容させていく動的なシステムとして視覚情報探索を理解できる可能性を示した。今後、同様の最適採餌理論に基づくアプローチが利用されている意思決定研究や、問題解決の選択肢や記憶などの内的な情報の探索を最適採餌理論の枠組みで捉えようとする研究、主体と環境の相互作用の中に人間の心を位置づけるエナクティヴィズムの研究との統合と発展を通して、探索を中心とした新たな認知観の構築が期待される。

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1. Introduction

1.1. Search

Search is the most prevalent activity in our daily life. It does not mean that we are always looking for a key in the living room, a cup in the kitchen, or a friend walking down the street. Rather, all of our actions are based on searching. Our actions are preceded by fixational eye movements (Hayhoe & Ballard, 2005; Land, 2009; Land & Hayhoe, 2001). For instance, when you are brewing a cup of coffee in the kitchen, your reaching out to a kettle should be preceded by fixation on the kettle. These eye movements, or overt attention, are a result of active scene viewing (Henderson, 2017). Without finding where the kettle is, we cannot engage in daily activities as ordinary as tea-making. We actively search in the environment for information relevant to the current task in order to accomplish chores that make up our lives.

1.2. Search in Visual Cognition Research

1.2.1. Visual Search Task

Traditionally, the search for visual information has been investigated with the visual search task. Originally developed as a tool to examine cognitive processes related to covert attention (the ability to select a part of visual information without overt eye movements), visual search research gained prominence when Neisser (1964) pointed out how easily we can find an object or person in a cluttered scene. For example, you can quickly spot a friend's face in a crowded platform while ignoring the faces of pedestrians passing by simultaneously. However, the ignored faces are still somehow processed and rejected as irrelevant for the search to be successful. These 'in-between' operations, occurring between not-seeing and seeing, represent the cognitive processes at play. Neisser (1964) proposed using the visual search task as a tool to decompose and analyze this information-processing hierarchy. To distinguish between searching for visual information and examining visual search as a task, I will refer to the former as 'visual information search' and the latter as the 'visual search task' throughout this paper.

With this task, previous research has focused on the inner workings during visual search, leading to the development of various models, including the feature integration theory (Treisman & Gelade, 1980) and guided search (Wolfe, 1994, 2007, 2021; Wolfe & Gancarz, 1997). In a typical visual search task, participants are tasked with locating a target stimulus among several distractors. A search display typically contains only one target stimulus. The number of stimuli on a display, referred to as 'set size,' varies depending on the purpose and design of the experiment. Once participants locate the target stimulus, they respond by pressing the corresponding key on the keyboard. For example, participants press the 'F' or 'J' key to indicate whether the target stimulus they found is tilted to the right or left.

The basic assumption of these theories is that too much information is fed into the cognitive system at one time during visual search, and processing everything in parallel is impossible. This assumption was supported by findings that searching times increase linearly as the number of visual stimuli on a search display increases (Egeth et al., 1984; Green & Anderson, 1956; Williams, 1966). Treisman & Gelade (1980) showed that the searching times increased linearly with the set size when the search target is defined by two features in conjunction, for example color and shape (‘green T’ rather than ‘green’). In contrast, the searching times did not increase with the set size when the search target is defined by a simple feature like color or shape. This result suggests that conjunction stimuli are processed serially, being processed one by one, while simple features can be processed in parallel.

These results can be explained by the feature integration theory (Treisman & Gelade, 1980). To find an object, basic features processed in parallel need to be integrated (Treisman, 1988, 1996). For example, we look for and see a tomato, not free-floating features of red and a circle. According to the theory, a spotlight of visual attention focuses on one spatial location of the map-like representation of the search scene (Crick, 1984; Eriksen & Eriksen, 1974; Eriksen & Hoffman, 1972). This spotlight cannot focus on two or more locations simultaneously (Eriksen & Yeh, 1985; Jans et al., 2010). Once attention selects the location, it retrieves the basic features that correspond to the object at this location. For example, if attention selects a green and vertical object, it then retrieves the color 'green' from the representation that maps the location of the colors in the search scene, and the orientation 'vertical' from the representation that maps the location of the orientation in the search scene. After retrieving the feature information, if it turns out that this selected location does not contain a target object, attention moves to and selects the next location. This process continues serially until the target object is found. Thus, the search for a conjunction stimulus is a serial process, and the search time increases linearly as the number of stimuli increases.

However, some types of conjunction searches were executed more efficiently than predicted by the feature integration theory. For example, in the second experiment in Wolfe et al. (1989), participants searched for a green and horizontal line among distractor stimuli. The distractor stimuli consisted of red and horizontal lines, and green and vertical lines. Since the target is defined as a conjunction of color and orientation, this is a conjunction search, and the search time should increase linearly as the set size increases. However, the slope of the search time as a function of the set size was shallower than predicted, especially when the number of stimuli was large.

The guided search theory by Wolfe et al. (1989) explained the results by proposing the mechanism that the representations mapping the basic features (feature maps) are used to ‘guide’ the serial allocation of visual attention in the conjunction search. In terms of color, stimuli in the search task were either red or green. Color is a basic feature, and, as shown in Treisman & Gelade's (1980) Experiment 1, the search time did not increase as the set size increased. Therefore, the feature maps of color can be processed in parallel. In this case, a feature map can divide the search stimuli into either red or green. If the target is green, it narrows down the stimuli that need to be searched serially to only the green stimuli. Thus, the slope of the search time was shallower than predicted by the feature integration theory.

The guided search theory greatly expanded the scope of the visual search task. On one hand, there has been a significant amount of research revealing the features that guide visual search. The guided search theory assumes that these guiding attributes are transmitted to the serial and attentive processing stage. Identifying these guiding attributes is thus necessary to complete the picture of visual processing, assuming the two-stage processes of parallel and serial stages. Basic features such as color (Nagy & Sanchez, 1990; Treisman & Gormican, 1988; Treisman & Souther, 1985), motion (Dick et al., 1987; Rosenholtz, 2001), orientation (Cavanagh et al., 1990; Foster & Ward, 1997; Wolfe et al., 1992), and size (Proulx & Green, 2011; Treisman & Gormican, 1988) were identified as being processed pre-attentively and guiding search. In addition to these definitive guiding attributes, the theory identified possible guiding attributes, including several doubtful cases (Wolfe & Horowitz, 2004, 2017).

On the other hand, it opened up the possibility of investigating more complex types of search. In addition to the guiding attributes related to the aspects of a target stimulus, other guiding attributes related to the aspects of a search environment have been identified. Scene guidance refers to the way syntactic or semantic scene structure guides search (Biederman et al., 1973, 1982). When looking for a mug in a kitchen, knowledge of the kitchen's structural layout guides the search, directing attention to the table or sink first, rather than the floor or wall. Scene search is guided by ‘gist,’ a rough overview of the structure of a scene. The gist is recognized briefly after the scene is presented. For example, global properties of a scene, such as navigability and openness, can be detected in a brief period under 50 ms (Greene & Oliva, 2009). Moreover, a very brief preview of the scene facilitates subsequent search (Castelhano & Henderson, 2007; Võ & Henderson, 2010). Considering this facilitation of search by the scene structure as guidance, visual search research has succeeded in incorporating search in a more realistic and naturalistic environment.

Search history is another guiding attribute that has gained prominence in recent years (Anderson et al., 2021; Awh et al., 2012). It has been well known that prior experiences facilitate visual search. The types of prior experiences that influence search vary greatly in terms of timescale. Within a trial, previewing a subset of distractor stimuli facilitates the search by inhibiting the previewed stimuli and prioritizing the rest of the stimuli (Watson & Humphreys, 1997). The phenomenon known as ‘priming of pop-out’ refers to the facilitation of visual search between a few trials by the repetition of the combination of colors of a target stimulus and distractor stimuli (Kristjánsson & Campana, 2010). Search is also sped up over the course of trials when spatial layouts of visual stimuli are repeatedly presented (Brockmole & Henderson, 2006; Chun & Jiang, 1998; Jiang & Wagner, 2004). Incorporating these properties as guiding attributes has integrated search in a naturalistic setting and search in a laboratory under one theory of comprehensive cognitive architecture.

1.2.2. Current Disparities and Challenges

Nonetheless, the studies above have more or less focused on the inner mechanisms, specifically on how the attentional spotlight searches within the representations created during visual search rather than the search itself. A curious contradiction arises from two assumptions that seem to underpin the research on visual information search. On one hand, there is a general assumption that a representation of the visual input is created, and a part of this representation is brought into awareness through the focus of attention. In this context, visual search appears to be an activity where attention is directed through the representation by various guiding attributes. Conversely, on the other hand, there is a general assumption that these same guiding attributes also influence behaviors in the real world. There is no reason to assume that a guiding attribute facilitating visual search in the representation also facilitates search behavior in the world, unless we assume that the representation and the world are the same entity.

Table 1

Four problems which biologists working on behaviors address

How?	**Mechanism** How does it work?	**Ontogeny** How did it develop?
Why?	**Function** What is it for?	**Phylogeny** How did it evolve?

1.3. The Development of an Integrated Framework

A framework that holds potential for addressing the behavior of searching for visual information itself is optimal foraging theory within the field of behavioral ecology. Foraging is the behavior in which animals search for food resources in response to the current environment (Kamil et al., 1987; Stephens et al., 2007). In Tinbergen's (1963) four questions on the problems of behavior in biology, optimal foraging theory falls into the category of the 'function' question (Table 1). In contrast to the 'mechanism' question, or how a certain behavior works, faced by experimental psychologists, the question concerns what the behavior is for, in terms of the current utility in an environment (Bateson & Laland, 2013). Focusing on adaptability to the current environment, answering this question should reveal the dynamic nature of search behavior in the world without relying solely on the concept of representation.

1.3.1. The Optimal Foraging Theory

The central tenet of optimal foraging theory is the maximization of the rate of energy intake during foraging (Emlen, 1966; MacArthur & Pianka, 1966). The maximization problems are classified into two distinct decisions: the patch-leaving problem and the diet-choice problem (Charnov, 1976a, b; Stephens & Krebs, 1986). The patch-leaving problem involves the decision of when animals should leave their current feeding area to search for food elsewhere. The diet-choice problem concerns the decision of what to choose during a search.

The optimal foraging theory consists of a set of mathematical models based on several assumptions (Stephens & Krebs, 1986). The most fundamental models include the patch-leaving model and the diet-choice model. These models share key concepts: search and encounter. During foraging, individuals search for prey while not detecting any. When they detect prey, they encounter it and cease searching. Upon encountering prey, foragers make two types of decisions: 1) whether to select this prey or continue searching, and 2) whether to leave the current environment and move to a new one. These decisions correspond to the diet-choice and patch-leaving decisions.

The analysis of the two decisions is based on the maximization of the net rate of energy intake. Let T_s represent the time spent searching for prey, and T_h represent the time spent handling prey, such as the time spent pursuing or consuming them. Therefore, the total time spent foraging can be expressed as:

$$T_f = T_s + T_h \tag{1}$$

Let E_f denote all the obtained energy (net energy) during foraging within the time T_f. The rate that foragers are assumed to maximize is defined as:

$$R = \frac{E_f}{T_s + T_h} \tag{2}$$

The amount of energy obtained in the environment depends on the rate of encounter. Let l represent the rate of encounter. Thus, the number of prey encountered is given by lT_s. Let $\bar{e}$ represent the average energy obtained per encounter, and $\bar{h}$ represent the average time spent handling per encounter. The relationships can be expressed as follows:

$$E_f = lT_s\bar{e}$$

$$T_h = lT_s\bar{h}$$

(3)

Substituting the expressions (2) results in:

$$R = \frac{lT_s\bar{e}}{T_s + lT_s\bar{h}}$$

(4)

By canceling out T_s, the rate we wish to maximize becomes:

$$R = \frac{l\bar{e}}{1 + l\bar{h}}$$

(5)

This equation is known as the Holling's disc equation (Charnov & Orians, 1973; Holling, 1965). While both the patch-leaving and diet-choice problems are grounded in this equation, they focus on different decisions. In the following sections, I will introduce both models in turn.

1.3.1.1. *The Patch-Leaving Problem*

The analysis of the patch-leaving problem is best known as the marginal value theorem proposed by Charnov (1976b). In this analysis, the unit of analysis is the time spent in a patch. A patch is a location or area where foragers can remain for a certain time interval, and it contains a concentration of specific prey (Charnov & Orians, 2006; MacArthur & Pianka, 1966). For simplicity in our algebraic model, we assume the availability of only one type of patch. Let $g(t_i)$ represent the gain function, which specifies the net energy obtained from a patch when foragers spend t_i units of time in the patch. At time $\hat{t}$, the rate that foragers seek to maximize is defined as follows:

$$R(\hat{t}) = \frac{lg(\hat{t})}{1 + l\hat{t}}$$

(6)

The gain function $g(t_i)$ can take various forms depending on the environment. According to Stephens & Krebs (1986), the gain function must satisfy the following conditions. First, when the time spent in a patch is 0, the net energy obtained in the patch is also 0:

$$g(0) = 0 \tag{7}$$

Second, the gain function must be initially increasing:

$$g'(0) > 0 \tag{8}$$

Third, the gain function must eventually exhibit negative acceleration. For all $t \geq \tilde{t}$, there exists some $\tilde{t}$ such that:

$$g''(t) < 0 \tag{9}$$

1.3.1.2. The Diet-Choice Problem

When faced with multiple options in an environment, individuals should take into consideration the relative costs and benefits associated with each option in order to make the most optimal choice. The optimal diet model offers an explanation for optimal behavior in such situations (Charnov, 1976b). This model defines optimal behavior as maximizing the rate of return. For instance, let's consider a scenario where tree A bears ripe apples with 10 units of energy and takes 5 seconds to obtain one fruit, while tree B offers unripe apples with five units of energy and takes 2 seconds to obtain one fruit. The rate-maximizing strategy would be to choose tree B, as 5/2 is greater than 10/5. Formally, the rate of the available n types of stimuli in an environment can be ranked as follows:

$$\frac{e_1}{h_1} > \frac{e_2}{h_2} > \cdots > \frac{e_n}{h_n} \tag{10}$$

In this formalization, e_i represents the gain obtained from acquiring a stimulus of type i, and h_i

represents the time necessary to handle the stimulus. The optimal strategy predicted by the model is to select a type j stimulus if the ratio $\frac{e_j}{h_j}$ is greater than the average rate of selecting all the other stimuli ranked below the type j stimulus. Generally, when the searcher finds a type i stimulus at rate l_i, the algorithm is expressed as follows.

$$\mathit{if\ the\ average\ rate}\ R = \frac{\sum_{i=1}^{j} l_i e_i}{1 + \sum_{i=1}^{j} l_i h_i} > \frac{e_{j+1}}{h_{j+1}},$$

$$\mathit{capture\ the\ type}\ j\ \mathit{stimulus}$$

(11)

Note that decisions in both the diet choice and patch-leaving problems depend on the search rate l_i, which is defined as the gain per unit of time. If the searcher takes longer to find nutritious type A stimuli but shorter to find less nutritious type B stimuli, it might be more efficient to search for easier-to-find type B stimuli. The difference lies in the decision variables of the models: in the patch-leaving problem, it is the time before moving to the next search location, whereas in the diet choice problem, the decision variable is whether to capture a type j stimulus. A comparison of the formalization of the average rate in the patch-leaving problem below and the diet choice problem above clearly illustrates these differences. The gain function $g(t_i)$ represents the expected gain, which corresponds to the energy intake in an animal's foraging activity, from the current patch after a specific duration of time t_i is spent searching in the patch.

$$R = \frac{\sum_{i=1}^{n} l_i g(t_i)}{1 + \sum_{i=1}^{n} l_i t_i}$$

(12)

1.3.2. Visual Foraging Task

A task was developed to apply the optimal foraging theory to research on visual information search. The visual foraging task and its variants have been used to expand the scope of visual search theories into more naturalistic contexts (Bella-Fernández et al., 2021; Smith & De Lillo, 2021). In a typical visual foraging task, participants are required to locate an unknown number of target stimuli within a display containing both target and distractor stimuli. For instance, Wolfe (2013) employed a task in which participants searched for target stimuli with varying shades of red. Participants received one point for correctly clicking on a target stimulus and were penalized one point for clicking on a non-target stimulus. After selecting as many target stimuli as desired within the current display, participants would transition to a new display. The search could continue until the allotted time expired.

Wolfe (2013) reformulated the human visual search task as a patch-leaving decision. This study showed that the marginal value theorem predicted visual foraging behaviors reasonably well, although there were some situations in which the behaviors deviated from optimality. Following Wolfe (2013), several studies have been conducted on visual foraging tasks to explore factors associated with performance in patch-leaving decisions in this context. These studies have revealed that the utilization of information in a foraging environment is an important factor in an optimal search (Zhang et al., 2017). If the quality of the search areas varies (Wolfe, 2013, Experiment 6) or if visual information cannot be relied upon (Wolfe, 2013, Experiment 5), human foraging behaviors are suboptimal.

The central issues related to both problems of optimal foraging are: (1) whether animals (including humans) behave optimally in search, and (2) if their behaviors deviate from optimal performance, what factors are responsible for this deviation? While research with the visual foraging task has focused on these questions, it has primarily addressed the patch-leaving problem. Despite the successful application of the patch-leaving problem, to the best of our knowledge, no research has been conducted on human visual search utilizing the diet-choice problem. The diet-choice problem involves making decisions among multiple options with varying values and search times. For instance, when one type of prey, A, is more nutritious but harder to find, while another type, B, is less nutritious but easier to find, how many A and B would a predator choose? Similar dilemmas arise in everyday life as well. We often encounter situations where we need to choose between healthier yet less affordable food options, such as fresh vegetables, and less nutritious but easily accessible alternatives like snacks.

Although previous studies utilizing the visual foraging task have often focused on examining the selection of stimuli with different values (Kristjánsson et al., 2014; Kristjánsson et al., 2020; Wolfe et al., 2018), the comprehensive investigation of the diet-choice component has been relatively limited. For instance, Kristjánsson et al. (2014) demonstrated a tendency among humans to consecutively select one type of stimuli before switching to an alternative type, drawing parallels to prey detection in animal foraging (Dukas & Ellner, 1993). However, while this discussion acknowledges the presence of the diet-choice problem, it primarily centers on the impact of attention constraints on the order of selection rather than directly addressing the diet-choice problem itself. Additionally, Wolfe et al. (2018) examined choice behaviors in the visual foraging task more directly by demonstrating a preference for more common types of stimuli over less common ones. However, the study did not explicitly differentiate between the patch-leaving and diet-choice components in the task, as participants were allowed to leave the current environment at their discretion.

1.4 Research Objectives

This thesis explores how to understand visual information search within the framework of the optimal foraging theory. The thesis comprises two studies. The first study demonstrates that the patch-leaving and optimal-diet problems involve distinct decision-making processes in visual foraging. This is illustrated by the distinct impact of blocking the learning of visual features of target stimuli on these two problems, respectively. The second study is centered on the diet-choice problem. It introduces a signal-detection diet-choice model, which is an enhancement of the classical diet-choice model. Additionally, the study examines how environmental changes influence behaviors in visual foraging, with a particular focus on analyzing deviations from the optimal decisions predicted by the signal-detection diet-choice model.

2. Study 1

The Influence of Blocking on Feature Learning and Optimal Decision in the Visual Foraging Task[1]

2.1. Introduction

Decisions regarding what to search for within the current display depend on whether observers can utilize cues that indicate the presence of a target stimulus. If targets are defined by a single feature, such as color, the association between the cue and the target can be quickly acquired. In a visual foraging task conducted by Wolfe (2013), the brightness of the stimulus color served as an indicator of rewards, allowing participants to easily find targets. Similarly, efficient search can be achieved when targets are defined by multiple features. Kristjánsson et al. (2014) demonstrated that participants could utilize these features to search in the visual foraging task, although efficiency decreased compared to targets defined by a single feature.

When multiple features are present in the search environment, the ability to distinguish cues that provide relevant information for a task from those that do not becomes crucial for efficient search. One approach to investigating this type of learning is through cue competition research. Blocking, an experimental procedure widely utilized in the literature on associative learning (Kamin, 1969), is a prominent example of cue competition. In brief, if a conditioned stimulus A (e.g., light) has previously been paired with a reward, there should be no evidence of subsequent learning of an additional conditioned stimulus B (e.g., noise) when presented as a compound stimulus with conditioned stimulus A. Several theories offer explanations for blocking. According to the Rescorla-Wagner model (Rescorla & Wagner, 1972), the associative strength of the additional stimulus B does not change when

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[1] This chapter is based on the paper that has been published as Kobayashi, H., Matsui, H., & Ogawa, H. (2023). The Influence of Blocking on Feature Learning and Optimal Decision in the Visual Foraging Task. *Journal of Experimental Psychology: Learning, Memory, and Cognition*.

presented as a compound with the previously learned stimulus A because the previously learned stimulus A perfectly predicts the presence of the reward, resulting in no prediction error upon adding the additional stimulus B. Blocking has been demonstrated in various species, including vertebrates (Beauchamp et al., 1991; Rodrigo et al., 1997; Waelti et al., 2001) and insects (Cheng & Spetch, 2001; Couvillon et al., 2001; Moreyra et al., 2020), in situations involving the decision of what to choose among multiple options.

Furthermore, the decision of what to choose is not the sole determinant of search efficiency. Observers must also learn to make decisions about when to leave the current environment in situations that involve both aspects. According to the marginal value theorem (MVT; Charnov, 1976a), the decision to leave the current environment relies on estimating the profitability of the current patch. The forager departs from the current patch when the estimate of the capture rate falls below the average capture rate for the entire environment. Previous studies have demonstrated that humans' decisions to leave a patch, including those in visual foraging (Kristjánsson et al., 2014; Kristjánsson et al., 2019; Kristjánsson & Kristjánsson, 2018; Wolfe, 2013), can be explained by models derived from the MVT. However, it remains unknown whether associative learning enhances the decision of when to leave the current environment in addition to the decision of what to choose.

Therefore, the current study aims to examine whether blocking occurs during visual foraging and its impact on the two aspects of foraging decisions. In a series of three experiments, we employed a visual foraging task where targets were defined by color and orientation. The experiments were designed to evaluate whether the features of a visual stimulus were blocked by another feature of the same stimulus. To investigate the influence of blocking on the decision of what to choose during search, we analyzed the probability of accurately clicking on targets, comparing the blocking group with the control group. Additionally, to explore the effect of blocking on the decision of when to leave the current environment, we calculated the optimal performance for each experiment and compared it with the actual performance of the participants.

2.2. Experiment 1

2.2.1. Methods

2.2.1.1. Participants.

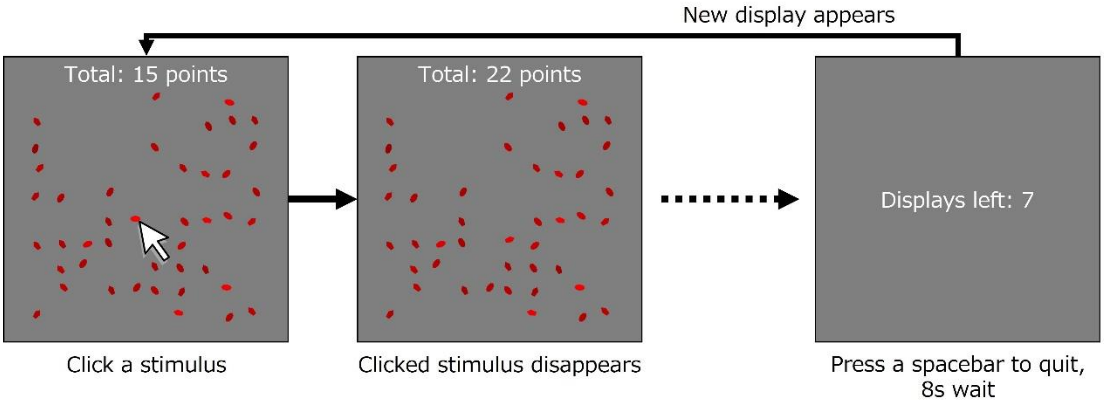
Twenty-three students at Kwansei Gakuin University participated in this experiment. All participants reported normal or corrected-to-normal vision. Written informed consent was obtained from all the participants prior to the experiment. All protocols were approved by Kwansei Gakuin University Committee for Regulations for Behavioral Research with Human Participant.

2.2.1.2. Materials and Procedures.

The experiment, including the instructions, was presented on a 24.5-inch monitor (ASUS ROG PG258Q). PsychoPy (Peirce et al., 2019) was used to program and control the experiments.The experiment consisted of two or three sessions depending on the experimental group to which the participant was assigned. At the beginning of each session, 40, 44, or 48 stimuli were presented on a gray background. The size of the stimuli was 0.27°×0.27° in the first session, and 0.27°×0.48° in the

Figure 1.

Stimulus configurations for Experiment 1



Note. Stimuli are magnified and modified for clarity of illustration**.**

other sessions. The stimuli were randomly presented on an invisible 10×10 grid. The size of each cell was approximately 2.28°×2.28°.

A schematic representation of the trial is illustrated in Figure 1. The task was to acquire as many points as possible by the end of each 10-minute session by clicking the stimuli. The participants were asked to move the mouse and click the stimuli. The clicked stimulus disappeared immediately. The sum of the points they accumulated by far in the session was presented in white letters in the upper-left corner of the screen; each time participants clicked a stimulus, this sum was updated. They were instructed to click as many targets as desired from the current screen until they clicked a box in the upper-left corner of the screen to finish the search on the current screen. When participants clicked on the box, the screen was replaced with one that told them the time remaining in the session. This screen lasted 8000 ms, and was then replaced by a new search screen, where new stimuli were presented in a different configuration. In Experiment 1, the number of screens participants could search was not limited.

Participants received or lost points, depending on the features of the clicked stimulus. These points were hypothetical, and the actual compensation for the experiment did not depend on the number of points received. Some of the stimuli were "good" stimuli or targets: participants could acquire points by clicking on it. The others were "bad" stimuli or distractors: participants lost points by clicking on them. We instructed participants to discover features that distinguished targets from distractors; these features differed from session to session. Participants were not told which features they should attend to.

There were two experimental groups: the blocking group and the control group. The participants in the blocking group completed three sessions: Color, Color/Orientation, and Orientation. The participants in the control group completed two sessions: Color/Orientation and Orientation. Twelve participants were assigned to the blocking group, and the remaining 11 participants were assigned to the control group.

All stimuli in the Color session were circles. In the Color/Orientation session and the Orientation session, stimuli were elongated pentagons and hexagons, presented in equal proportions in each display. In the Color session, targets were more reddish than the distractors. In the Color/Orientation session, good stimuli were more reddish and slanted towards the horizontal than bad stimuli. In the Orientation session, targets were slanted more than the bad stimuli. Thus, participants had to learn to select different feature dimensions (color or orientation) in different sessions. This procedure was intended to ensure that the blocking phenomenon in associative learning would occur; that is, learning in the initial Color session was expected to disturb subsequent learning of orientation in the blocking group. By contrast, this disturbance of subsequent learning should not occur in the control group, who learned both color and orientation in their initial session.

In each search screen, eight or nine stimuli were the targets. To determine the points, colors, and orientations of the targets and distractors, the numbers were drawn from two overlapping normal distributions (Figure 2). For targets, eight or nine numbers were drawn from the normal distribution with a mean of 0.8 and a variance of 0.1 and were converted to stimulus intensity (redness or degrees of slant) according to the rules described below. Similarly, for distractors, numbers were drawn from the normal distribution with a mean of 0.4 and a variance of 0.1. If a number larger than 1 was sampled, 1 was substituted for this number. Similarly, if a number less than zero was sampled, zero was substituted for this number.

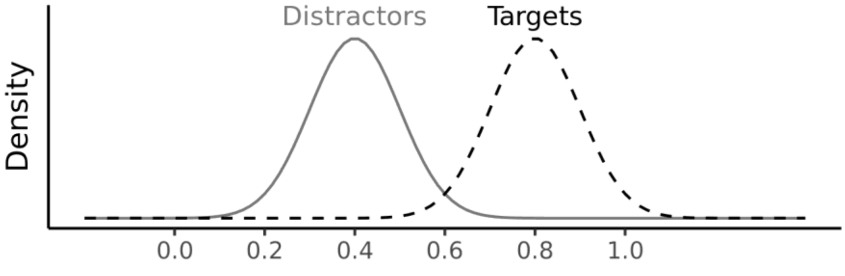
These numbers were used to determine the intensity of the red stimuli in the first two sessions. In PsychoPy, the RGB color space is represented as a triplet of values ranging between -1 and 1, and red is coded as [1.0, -1, -1]. This corresponds to RGB representation [255, 0, 0]. The redness of the stimuli can be manipulated by varying the first element from 1 to -1. For example, if the sample number was 0.8, the color of one of the good stimuli was coded as [0.8, -1, -1].

The same numbers were used to determine the orientations of the stimuli in the Color/Orientation and Orientation sessions. Half of the sampled numbers were multiplied by 90, and the remaining half were multiplied by -90. Larger sampled numbers correspond to orientations closer to 90° or 270°. Consequently, the color and orientation of a stimulus were correlated; if a stimulus was redder, it was slanted and closer to the horizontal. The orientations of stimuli in the orientation session were similarly determined, and the color of all stimuli was orange, coded as [1, 0, -1].

The same numbers were used to determine the points on the stimuli. Thus, by clicking on each stimulus, participants received points corresponding to the color and orientation of the stimulus. However, the correspondence was imperfect because these numbers were drawn from the overlapped distributions. For the targets, the points were calculated by multiplying each sampled number by 10. The participants received this number of points if the clicked stimulus was a target. For example, if the number 0.8 was sampled, participants received eight points if the stimulus was a target. For distractors, the points were calculated by subtracting each sampled number from 1 and multiplying by

Figure 2

The distributions from which the points, colors and orientations of targets and distractors were drawn



10. For example, if the number 0.2 was sampled, participants lost eight points if the clicked stimulus was a distractor.

2.2.1.3 Analysis

The analysis of this experiment is presented in three sections. First, the initial analyses report the median number of patches visited, targets encountered throughout the session, and targets encountered in a patch, as well as the median residence time in a patch. The initial analyses were conducted with the descriptive purpose of examining general performance on the task using conventional metrics without a strong prior hypothesis. We then report the analyses of the reaction times and accuracy. These analyses were performed to assess the occurrence of blocking. Therefore, we used linear mixed models to compare the performance of the blocking and control groups in the final orientation session.

Initial analysis, data processing, and visualization were performed using R language v4.1.0. To compare reaction time and accuracy, we used the lmerTest package (Kuznetsova et al., 2017) for linear mixed models and the glme package (Weerahandi et al., 2021) for general linear mixed models.

2.2.2. Results

2.2.2.1. Initial Analyses

Color Session. Participants visited a median of 15 patches and encountered 129 targets throughout the session. In each patch, the participants found a median of 8 targets. The median residence time were 18.31 s.

Color/Orientation Session. Participants in the blocking group visited a median of 20 patches and encountered 172 targets throughout the session. Participants in the control group visited a median of 17 patches and encountered 148 targets throughout the session. In each patch, participants in both groups had a median of 8.5 targets. The median residence time of the blocking group was 11.96

s, and the median residence time of the control group was 8.92 s.

Orientation Session. Participants in the blocking group visited a median of 18.5 patches and encountered 37.5 targets throughout the session. Participants in the control group visited a median of 15 patches and encountered 105 targets throughout the session. In each patch, participants in the blocking groups had 2.75 targets, and participants in the control group had seven targets. The median residence time of the blocking group was 15.50 s, and the median residence time of the control group was 11.67 s.

2.2.2.2. Comparison: Blocking and Control Groups[2]

The response time between the clicks and the accuracy is shown in Figure 3. To assess whether blocking had occurred, we compared the performance of the blocking and control groups in the color/orientation and orientation sessions. If blocking occurred, the response time between clicks would be longer and the accuracy of the blocking group would be lower than that of the control group. In addition, a difference in performance should occur from the beginning of the orientation session if the control group successfully learned about the value of orientation, but the blocking group did not learn it.

Thus, we conducted an analysis using a linear mixed model for response time. To compare the performance in the first and second halves of the sessions, we split the data of each participant into two epochs, each containing data from either the first or the second half of the session. We included epoch, session, and group as fixed effects, and included both the random intercept and slopes. For random slopes, we modelled the effect of the groups varied by participant. We did not include a random slope for the phases, because the model did not converge. The result of the model indicated that response times in the orientation session were on average an estimated 1710.74 ms slower in the

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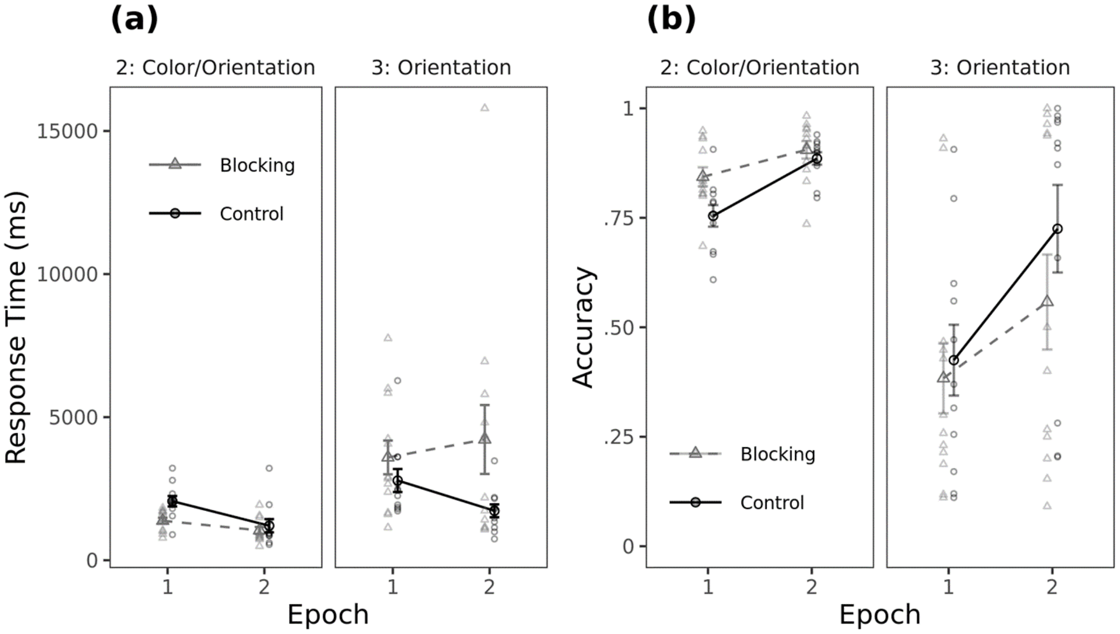
[2] This analysis was not originally planned in Experiment 1 and Experiment 2. We thank the anonymous reviewer for suggesting an appropriate approach to compare the performance of the blocking and control groups.

blocking group than in the control group ($\hat{\beta}$ = -1710.74, *SE* = 730.16, *t* = -2.34, *p* = .03). The three-way interaction was not statistically significant ($\hat{\beta}$ = -414.06, *SE* = 266.61, *t* = -1.55, *p* = .12).

We then conducted an analysis using a generalized linear mixed model for accuracy. We included session, group, and epoch as the fixed effects. The model included both random intercepts and slopes. For random slopes, we modelled the effects of sessions and groups that varied by participants. The results of the model indicated that the accuracy in the orientation session was lower than that in the color/orientation session ($\hat{\beta}$ = -2.25, *SE* = 0.53, *z*= -4.26, *p* < .001). In the orientation session, the accuracy in epoch 2 was higher than that in epoch 1 ($\hat{\beta}$ = 1.09, *SE* = 0.27, *z*= 3.99, *p* < .001), indicating that learning of the target feature occurred in the orientation session. No other interactions were found to be statistically significant.

Figure 3

Response time and accuracy (the ratio of accurately clicking target stimuli) in Experiment 1.

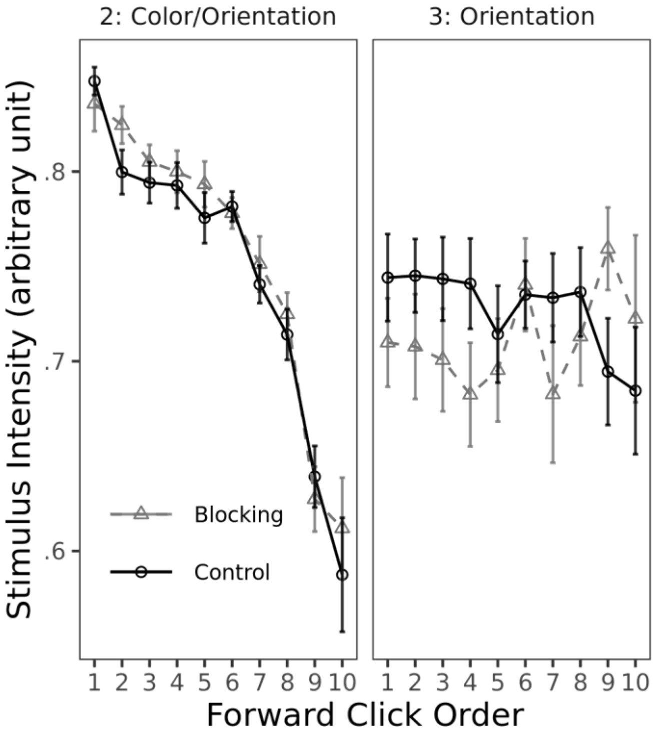


Note. Each panel corresponds to the Color/Orientation and Orientation sessions. The error bars represented standard errors.

The results of the linear mixed model on response times indicated that the blocking procedure disturbed the search during the orientation session. However, the results of the generalized mixed model for accuracy were not consistent with this conclusion. The possibility is that the blocking group responded more cautiously than the control group. Indeed, the blocking group clicked on an average of 4.45 stimuli in a patch during the orientation session. By contrast, the control group clicked on an average of 7.28 stimuli. This cautious strategy could result in longer response times. This possibility of a speed-accuracy tradeoff was examined in Experiment 2.

Figure 4

The stimulus intensity of clicked stimuli as a function of the clicking order in Experiment 1.



Note. In the Color/Orientation session, the stimulus intensity means the redness and orientation of the stimuli. In the Orientation session, the stimulus intensity means the orientation of the stimuli.

2.2.2.3. Behavioral Analysis: The Stimulus Intensity

We examined how blocking affected the patch performance. To this end, we first showed the intensity of the clicked stimuli as a function of forward click order (Figure 4). In this figure, Position 1 is the first click on a patch. Because the time when each participant left a patch varied and a few participants stayed in a patch for a very long time, we only showed the first 10 clicks. The stimulus intensity represents the redness or slant of the stimuli, and higher values indicate that the stimuli were redder or more horizontal.

We conducted an exploratory analysis using a linear mixed model, where participants were included as random intercepts and sessions as random slopes. The two-way interaction of the session and click order was significant, showing that the stimulus intensity in later clicks (from the 6th to 10th click) was higher in the color/orientation session than that in the orientation session (all *p*s < .001). The difference between the sessions was due to the pattern of performance in the color/orientation session. In this session, participants clicked on the stimuli that they were certain to be good first and moved to less certain stimuli in later clicks. By contrast, performance did not show this pattern in the orientation session in either group.

In summary, the results of Experiment 1 revealed that the blocking procedure resulted in longer reaction times in visual foraging, with prior learning of the color impeding subsequent learning of the orientation dimension. However, the longer response times of the blocking group in the orientation session may have resulted from procedural pitfalls. Experiment 1 was performed without any limitations on the number of patch leavings, which may have allowed participants to leave the patch before they sufficiently explored it, resulting in missed chances of learning the contingency between points and features. In addition, the longer response times and small number of clicks may have resulted from a more cautious strategy adopted by the blocking group. To examine this possibility, we conducted Experiment 2, in which the maximum number of patch leavings was limited in each session.

2.3. Experiment 2

2.3.1. Method

2.3.1.1. Participants

Twenty students in Kwansei Gakuin University participated in the experiment. All patients reported normal or corrected-to-normal vision. Written informed consent was obtained from all the participants prior to the experiment.

2.3.1.2. Materials and Procedures

The materials, procedure, and analysis were the same as those in Experiment 1, except for the following points. First, ten participants were assigned to the blocking group and the other ten to the control group. Second, the number of moves between patches was limited to 16. If the participants tried to move for the seventeenth time, the session ended, even if the time in the session remained. The participants were informed of the maximum number of patch leavings before the experiment. Thus, unlike Experiment 1, the procedure encouraged the exploration of the current patch because leaving it hastily resulted in lower profits.

2.3.2. Results

2.3.2.1. Initial Analyses

Color Session. Participants visited a median of 16 patches and encountered 127.5 targets throughout the session. In each patch, the participants had 8 targets. The median residence time was 28.12 s.

Color/Orientation Session. Participants in the blocking group visited a median of 16 patches and encountered 127.5 targets throughout the session. Participants in the control group visited a median of 16 patches and encountered 123.5 targets throughout the session. In each patch, participants in both groups had 8 targets. The median residence time of the blocking group was 32.54 s and that of the control group was 26.36 s.

Orientation Session. Participants in the blocking group visited a median of 16 patches and encountered 53 targets throughout the session. Participants in the control group visited a median of 15.5 patches and encountered 90.5 targets throughout the session. In each patch, participants in the blocking group had 3.5 targets, and those in the control group had 6.5 targets. The median residence time of the blocking group was 34.06 s and that of the control group was 36.29 s.

2.3.2.2. Comparison: Blocking and Control group

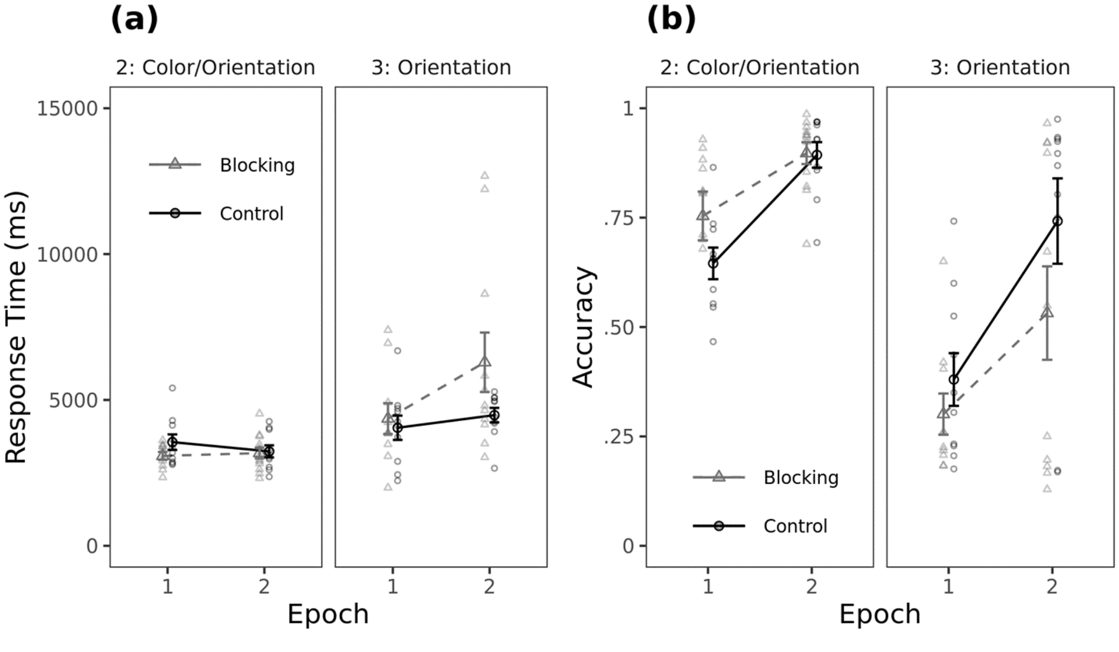
The response time between the clicks and the accuracy is shown in Figure 5. To assess whether blocking had occurred, we compared the performance of the blocking and control groups in the color/orientation and orientation sessions.

As in Experiment 1, we conducted an analysis of the response times between clicks using a linear mixed model. We split the data of each participant into two epochs, each containing data from the first or second half of the session. We included session, group, and epoch as the fixed effects. The model included both random intercepts and slopes. For random slopes, we modelled the effects of sessions and groups that varied by participants. The result of the model indicated that response times in the epoch 2 were on average an estimated 455.54 ms faster than in the epoch 1 ($\hat{\beta}$ = -455.54, SE = 190.30, t = -2.39, p = .02). No statistically significant interactions were found. Responses were faster later in the session than at the beginning of the session, and the control and blocking groups both showed this pattern of performance.

We then conducted an analysis of accuracy using a generalized linear mixed model. We included session, group, and epoch as the fixed effects. The model included both random intercepts and slopes. For random slopes, we modelled the effects of sessions and groups that varied by participants. The results of the model showed that the accuracy for the orientation session was higher in the control group than in the blocking group ($\hat{\beta}$ = 1.29, *SE* = 0.49, *z* = 2.67, *p* = .008). Accuracy for the orientation session was higher in Epoch 2 than in Epoch 1 ($\hat{\beta}$ = 0.77, *SE* =0.21, *z* = 3.76, *p* < .001). However, the three-way interaction was not statistically significant ($\hat{\beta}$ = -0.26, *SE* = 0.28, *z* = -0.92, *p* = .35). Overall, the control group performed more accurately than did the blocking group during the orientation session. Although the performance improved from the first to the second half of the orientation session, the rate of learning did not differ between the control and blocking groups.

Figure 5

Response times and accuracy (the ratio of accurately clicking target stimuli) in Experiment 2



Note. Each panel corresponds to the Color/Orientation and the Orientation session. The error bars represented standard errors.

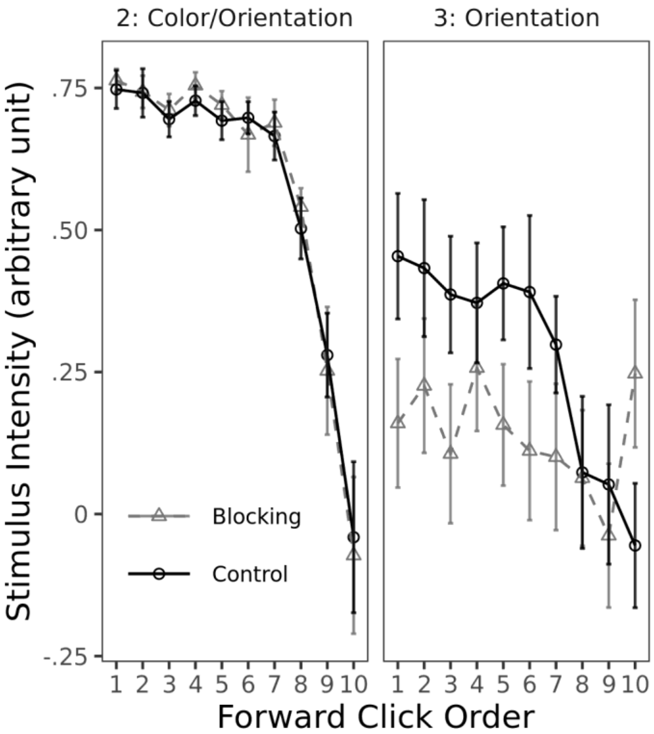
2.3.2.3. Behavioral Analysis: The Stimulus Intensity

We examined how blocking affected the performance of a patch by analyzing changes in the stimulus intensity of the clicked stimuli (Figure 6). As in Experiment 1, a linear mixed model was conducted with participants as random intercepts and sessions as random slopes. The effect of the clicking order was statistically significant from the 6th to 9th click (*p*s < .05), implying that the stimuli clicked at these positions were less valuable than at the first click. The two-way interaction between the session and clicking order was statistically significant ($\hat{\beta}$ = 0.39, *SE* = 0.09, *t* = 4.19, *p* < .001), showing that the stimulus intensity at the 9th click was higher in the orientation session than in the color/orientation session. No interaction between the groups was statistically significant. Overall, the participants conducted the task by first clicking on valuable stimuli and then moving them to less valuable stimuli. As in Experiment 1, no difference between the groups in the orientation session was observed, suggesting that both groups used the same approach to the task. Although blocking disturbs the performance, as observed in the accuracy analysis, it was not apparent how it affected the behaviors during the search in a patch.

Moreover, there is an unideal aspect of the experimental procedure that should be addressed properly. In Experiments 1 and 2, the control group experienced only two sessions, whereas the blocking group experienced three sessions. This procedure was not ideal because any results observed in these experiments could be due to the difference in the amount of training. For example, the control group responded more accurately in the orientation session than did the blocking group, probably because the blocking group was fatigued by longer experimental sessions and did not focus on the task. Furthermore, it is also possible that the control group did not experience enough tasks before the orientation session, which could have resulted in poorer performance than expected. Indeed, we did

Figure 6

The stimulus intensity of clicked stimuli as a function of the clicking order in Experiment 2



Note. In the Color/Orientation session, the stimulus intensity means the redness and orientation of the stimuli. In the Orientation session, the stimulus intensity means the orientation of the stimuli.

not observe statistically significant differences between the control and blocking groups when we compared the intensity of the clicked stimuli. In summary, the difference in the amount of training could be a confounding variable in Experiments 1 and 2. Thus, we conducted Experiment 3, in which the number of sessions was equal between the control and blocking groups.

2.4. Experiment 3

2.4.1. Method

2.4.1.1. Participants

Forty-two students in Kwansei Gakuin University participated in the experiment. Based on the results of Experiment 2, we conducted simulation-based power analysis using the R package mixedpower (Kumle et al., 2021). To reach a power of 0.8, for the three-way interaction between the groups, the sessions, and the epochs (the former or latter half of the sessions), we would need approximately 40 participants. All participants reported normal or corrected-to-normal vision. Written informed consent was obtained from all the participants prior to the experiment.

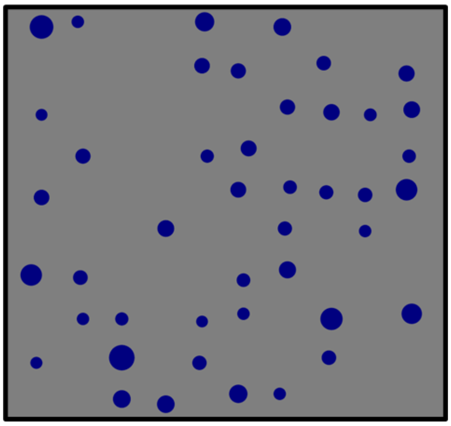
2.4.1.2. Materials and Procedures

The materials, procedure, and analysis were the same as those in Experiment 2, except for the following points. To balance the amount of training between the groups, both the control and blocking groups underwent three sessions. The procedure for the blocking group was the same as that used in Experiment 1. The control group experienced the size session at the beginning of the experiment, instead of the color session for the blocking group.

In the size session, larger stimuli were more likely to be associated with gains, while smaller

Figure 7

An example of a stimulus configuration in the Size session for the control group in Experiment 3



Note. Stimuli are magnified and modified for clarity of illustration.

stimuli were more likely to be associated with losses (Figure 7). As in Experiments 1 and 2, the size of each stimulus was determined by a number sampled from the two overlapping normal distributions. If a stimulus had a sampled value of x, the size of the stimulus was $0.48x°×0.48x°$. If the clicked stimulus was a target with a value of x, the participant received $10x$ points. If the clicked stimulus was a distractor, the participant lost $(1-x)\times 10$ points.

2.4.2. Results

2.4.2.1. Initial analyses

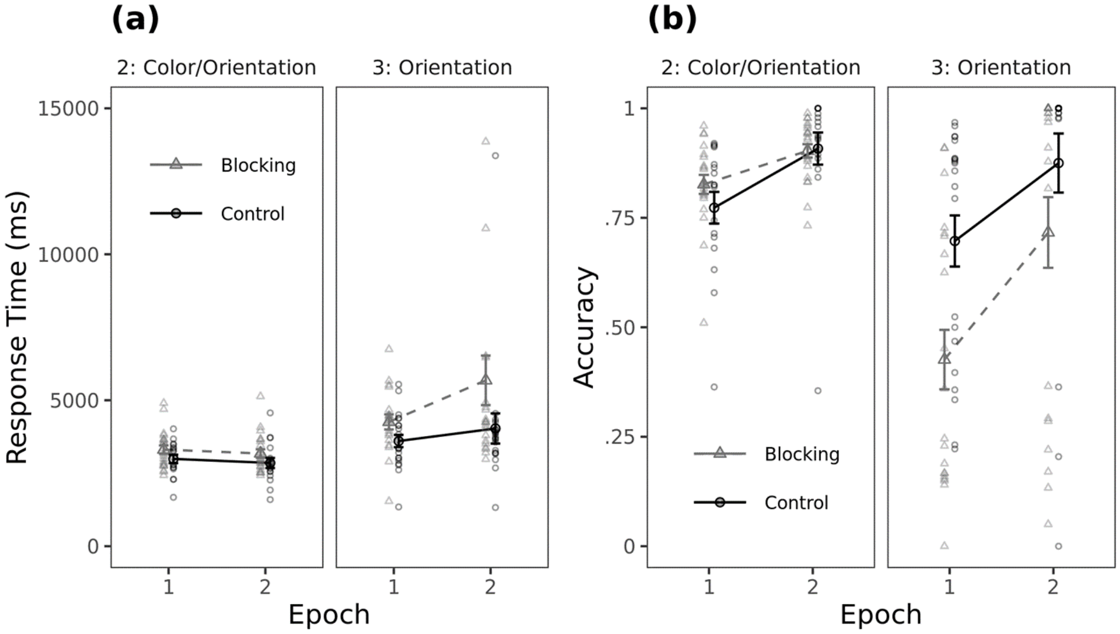
Color or Size Session. The participants in the blocking group had a median of 103 targets throughout the session. The participants in the control group had a median of 130 targets throughout the session. In each patch, participants in the blocking groups found a median of eight targets and participants in the control group found a median of eight targets. The median residence time of the blocking group was 31.0 s, and the median residence time of the control group was 28.7 s.

Color/Orientation Session. The participants in the blocking group encountered a median of 129 targets throughout the session. The participants in the control group had a median of 129 targets throughout the session. In each patch, participants in both groups had 8 targets. The median residence time of the blocking group was 29.2 s, and that of the control group was 26.8 s.

Orientation Session. The participants in the blocking group had 103 targets throughout the session. The participants in the control group had 130 targets throughout the session. In each patch, participants in the blocking groups had eight targets and participants in the control group had eight targets. The median residence time of the blocking group was 32.7 s, and the that of the control group was 30.7 s.

Figure 8

Response times and accuracy (the ratio of accurately clicking target stimuli) in Experiment 3



Note. Each panel corresponds to the Color/Orientation and Orientation sessions. The error bars represented standard errors.

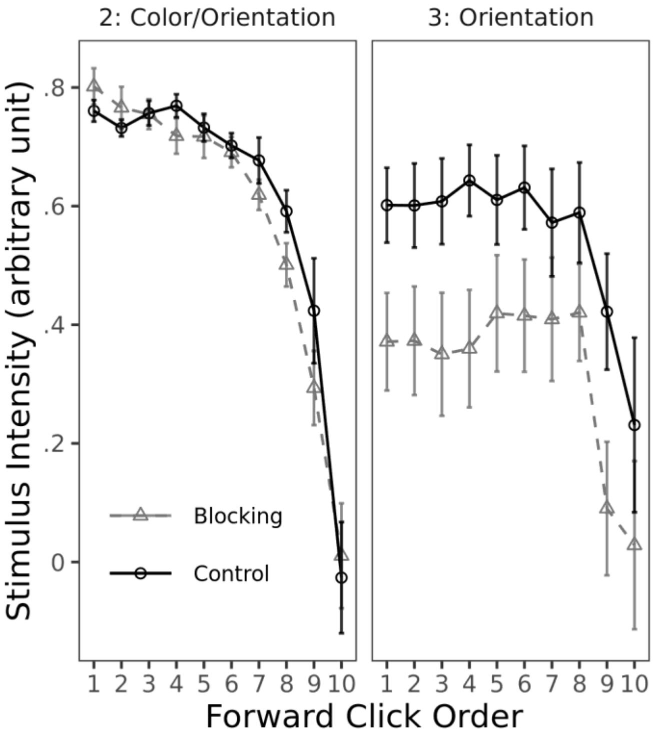
2.4.2.2. Comparison: Blocking and Control group

The response time between the clicks and the accuracy is shown in Figure 8. To assess whether blocking had occurred, we compared the performance of the blocking and control groups in the color/orientation and orientation sessions.

As in Experiments 1 and 2, we conducted an analysis of the response time between clicks using a linear mixed model. We split the data of each participant into two epochs, each containing data from the first or second half of the session. We included session, group, and epoch as the fixed effects. The model included both random intercepts and slopes. For random slopes, we modelled the effects of sessions and groups that varied by participants. The results of the model showed that response time

Figure 9

The stimulus intensity of clicked stimuli as a function of the clicking order in Experiment 3



Note. In the Color/Orientation session, the stimulus intensity means the redness and orientation of the stimuli. In the Orientation session, the stimulus intensity means the orientation of the stimuli.

in Epoch 1 of the orientation session was on an average of 671.74 ms faster for the control group than for the blocking group ($\hat{\beta}$ = -671.74, *SE* = 246.78, *t* = -2.72, *p* = .009). The difference between the response times of the blocking and control groups in Epoch 2 was not statistically significant ($\hat{\beta}$ = -187.58, *SE* = 218.99, *t* = -0.86, *p* = .39)

We then conducted an analysis of accuracy using a generalized linear mixed model. We included session, group, and epoch as the fixed effects. The model included both random intercepts and slopes. For random slopes, we modelled the effects of sessions and groups that varied by participants. The results of the model showed that the accuracy for the orientation session was higher in the control group than in the blocking group ($\hat{\beta}$ = 1.76, *SE* = 0.54, *z* = 3.28, *p* = .001). The three-way interaction was not statistically significant ($\hat{\beta}$ = -0.58, *SE* = 0.31, *z* = -1.89, *p* = .06), implying that the accuracy for the control group was generally higher in Epoch 2 of the orientation session than in the blocking group.

Overall, the results of Experiment 3 are consistent with those of Experiment 2. A difference in accuracy between the blocking and control groups in the orientation session showed that blocking had occurred. Specifically, the blocking group made more inaccurate clicks in the orientation session than the control group. The blocking group also responded more slowly during the first half of the orientation session than the control group. This indicated that a disturbance of learning of the blocking group during the color/orientation session was reflected in these differences.

It is worth noting that the performance during the Orientation phase exhibited greater variation compared to the Color/Orientation phase, primarily due to the poorer performance of certain participants. This observation is consistent with previous research demonstrating less efficient search for orientation compared to color (Huang, 2015). While incorporating participants as a random effect in the linear mixed model may have somewhat alleviated these variations, it is important to acknowledge the presence of individual differences in this task, which should be considered in future research.

A concern regarding this interpretation is that we cannot exclude the possibility that the disturbance of learning occurred not during the Color/Orientation session, but rather during the Orientation session. Since the current experiments did not include an extinction session where participants received no rewards for clicking on target stimuli, there was always a chance for participants in the blocking group to newly learn the orientation as a cue during the Orientation session. To address this issue, we have plotted the accuracy of clicking on target stimuli in each display (see Appendix 1) and in the initial displays (see Appendix 2) of the Color/Orientation and Orientation phases. These figures suggest that the blocking group performed poorer than the control group in the initial display of the Orientation session, particularly in Experiment 3 where the methodological issues were resolved. This difference in performance at the beginning of the Orientation phase indicates that there was indeed a disturbance in learning the orientation as a cue for the blocking group during the Color/Orientation phase.

2.4.2.3. Behavioral Analysis: The Stimulus Intensity

We examined how blocking affected the performance of a patch by analyzing changes in the intensity of clicked stimuli. The stimulus intensity of clicked stimuli is shown in Figure 9. As in Experiments 1 and 2, a linear mixed model was conducted with participants as random intercepts and sessions as random slopes. The effect of the clicking order was statistically significant, showing that the stimulus intensity was lower in later clicks (from the 4th to 10th clicks) than in the first click ($p < .005$). The three-way interaction between session, clicking order, and group was significant. For the blocking group, the stimulus intensity of clicked stimuli was higher in the color/orientation session than in the orientation session, from the 1st to 7th clicks (ps < .006), but lower in the color/orientation session than in the orientation session at 10th click ($\hat{\beta} = 0.21$, $SE = 0.97$, $t = 2.24$, $p = .03$). For the control group, the stimulus intensity at the 9th click was higher in the orientation session than in the color/orientation session ($\hat{\beta} = 0.22$, $SE = 0.65$, $t = 2.48$, $p = .02$).

Overall, performance in the blocking group differed from that in the color/orientation session to the orientation session. Specifically, in the color/orientation session, both the control group and the blocking group clicked more valuable stimuli first, and stimuli with lower values were clicked later in a patch, before leaving the patch altogether. However, the blocking group clicked on stimuli with lower values at the first click in a patch of the orientation session. This could have resulted from a lack of learning in the blocking group. Without knowing which feature to select, the blocking group cannot adopt the strategy of clicking valuable stimuli first. These results suggest that blocking disturbed the learning of features that defined targets and affected search behaviors in a patch.

2.4.2.4. The Analysis on the Optimality of Visual Foraging

We reported an analysis intended to supplement the results of the analyses of reaction times and accuracy. In Experiments 2 and 3, blocking resulted in lower probability of accurately clicking target stimuli in the visual foraging task. These results were consistent with previous studies that have shown a reduced rate of selecting targets in foraging due to blocking. However, foraging consists of more than selecting individual targets. It also encompasses decisions regarding when to leave the current environment, which may be influenced by blocking as well. Therefore, we conducted an additional analysis using the optimal foraging theory to examine the impact of blocking on patch-leaving decisions.

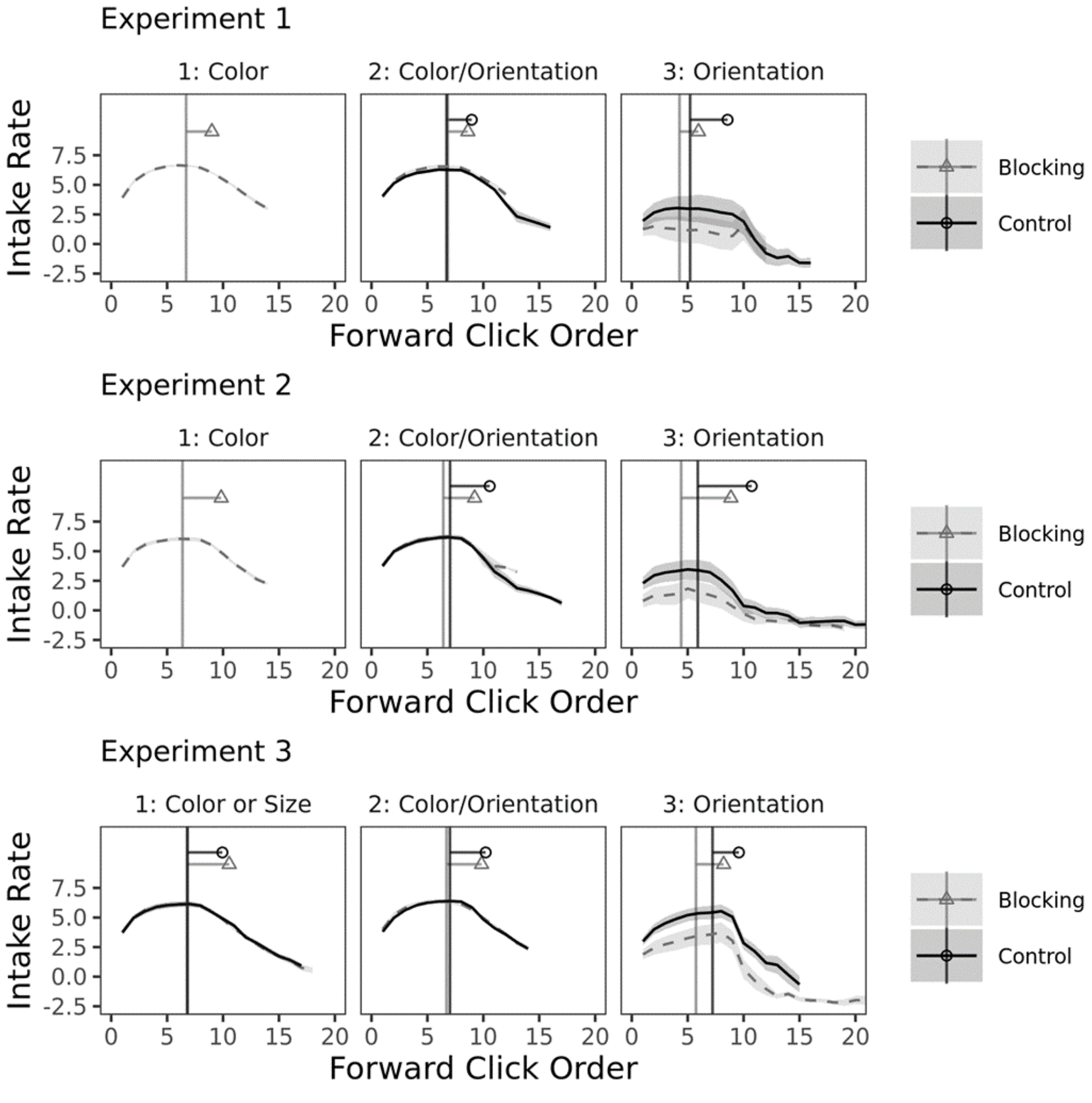
In optimal foraging theory, the objective in patch-leaving decisions is to maximize the average rate of energy intake R, which is formulated as follows:

$$R_i = \frac{\sum g(t_i) - s}{1 + \sum t_i} \tag{13}$$

The equation is a simplified version of the marginal value theorem (Charnov, 1976a) and has two assumptions: 1) there is only one type of patch and 2) there is only a time cost s, and no

Figure 10

Simulations of the optimal patch-leaving time based on the marginal value theorem and the actual patch-leaving time



Note. The curves represent the simulated average rate of energy intake *R*. The vertical lines show the optimal leaving times for the blocking and control groups. The triangles and circles show the actual leaving times of the blocking and control groups, respectively.

energy cost associated with moving from one patch to the next. We simulated the above equation using participants' data from the three experiments. The number of points that the participants received in the i-th click in the patch was inserted as $g(t_i)$, and the number of clicks was used as t_i. The results of the simulations are shown as curves in Figure 4. The optimal patch-leaving times are represented as vertical lines.

Figure 10 shows the mean actual departure time. The triangles and circles represent the blocking and control groups, respectively. In all conditions of each experiment, the mean patch-leaving time was later than that predicted by optimal foraging theory. One-sample t-tests showed that the deviations of the actual leaving time from the optimal leaving time were larger than zero in all conditions (*p*s < .01). An overstaying tendency was observed in both the blocking and control groups in the final orientation session. There was no statistically significant difference in the actual leaving time of either group in any of the experiments (*t*(21) = -1.48, *p* = .15; *t*(19) = -0.25, *p* = .80; *t*(40) = 0.11, *p* = .91), suggesting that blocking did not affect the leaving time even when it disturbed performance.

The tendency to overstay has been reported in various foraging tasks, including visual foraging tasks (Wolfe, 2013), other types of human foraging tasks (Constantino & Daw, 2015; Harhen & Bornstein, 2023; Hutchinson et al., 2008), and animal foraging behaviors (Hayden et al., 2011; Kane et al., 2021). Harhen & Bornstein (2023) demonstrated through computational modeling that the tendency to overstay is attributed to the uncertainty stemming from making inferences about the future environment. The current findings indicate that blocking did not impact the timing of the patch-leaving decisions. These results suggest that the decisions regarding when to leave a patch were made independently of target selection, which was disrupted by blocking.

2.4.2.5. The Analysis on the Optimality of Search Path

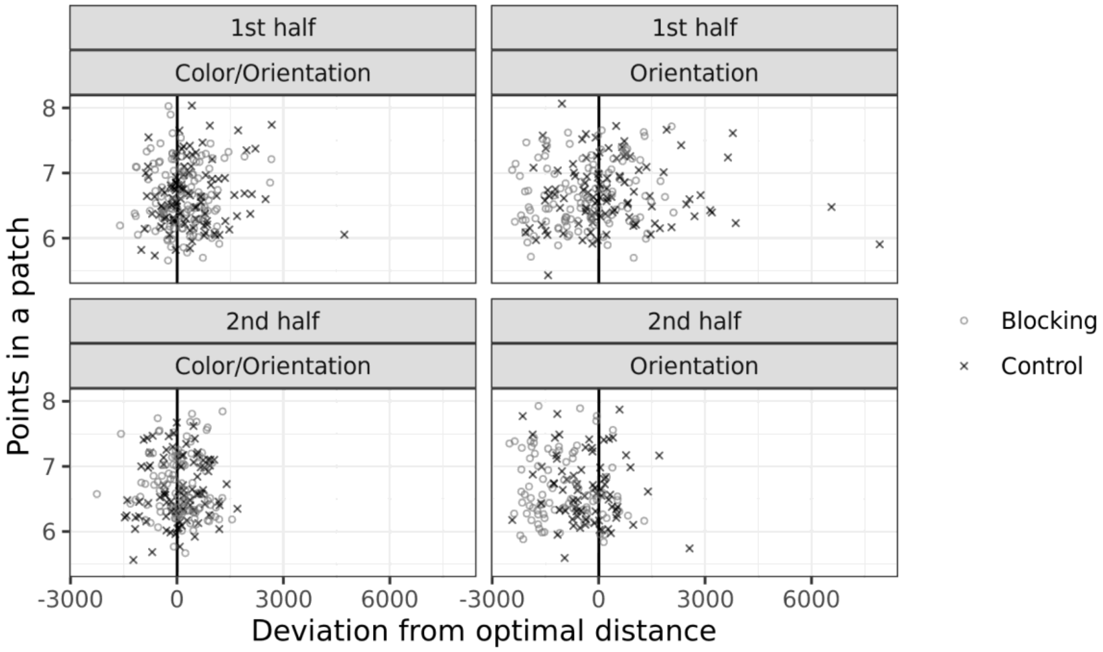
When the environment is structured (De Lillo et al., 1998) or memorized (Cramer &

Gallistel, 1997), monkeys avoid revisiting sites and reduce the traveling distance during search. While visual search shares a spatial aspect with animal foraging, previous studies did not consider the traveling distance as a fundamental feature of the search. In this study, we utilized the traveling distance to assess the efficiency of search in the visual foraging task from a spatial perspective. For this purpose, we calculated the shortest search path for visiting all the target stimuli. When the set of target stimuli (vertices) V = {1, 2, ..., n} and the distances between each pair of stimuli $d_{i,j}$ (i,j $\in$ V) are given, the function to minimize is as follows:

$$\sum_{i,j\in V} d_{i,j}x_{i,j}$$

Figure 11

Deviation of the length of actual search paths from the optimal search distance for the color/orientation and orientation sessions in Experiment 1



Note. The upper panels showed the first half of each session, and the lower panels showed the second half of each session. The vertical lines represent the optimal search distance.

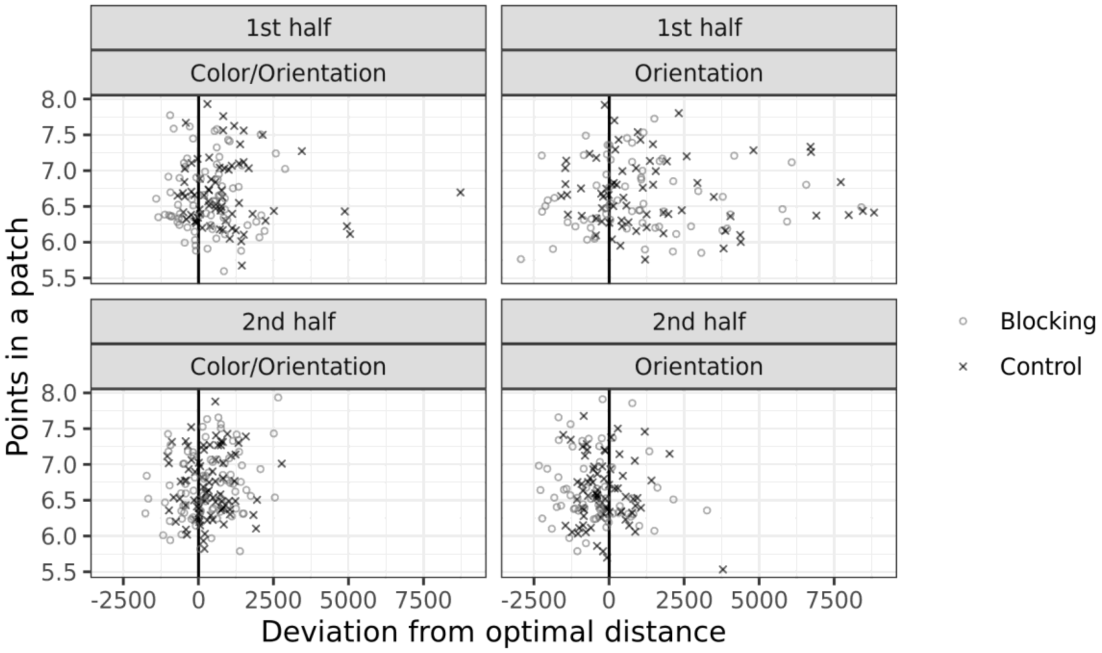
(14)

where x is a variable that takes the value of 1 when a certain path passes between stimuli i and j and 0 otherwise. The optimal path was calculated using the JuMP package in Julia (v1.6.1). Data processing and visualization were performed using R v4.1.0.

To examine the divergence from shortest performance, we first calculated the lengths of the shortest search trajectories, followed by the lengths of the actual search trajectories. We then subtracted the actual lengths from the shortest lengths and used these values as a measure of the divergence from shortest performance. Negative values indicate that the observed search path is shorter than the length of the shortest path.

Figure 12

Deviation of the length of actual search paths from the optimal search distance for the color/orientation and orientation sessions in Experiment 2

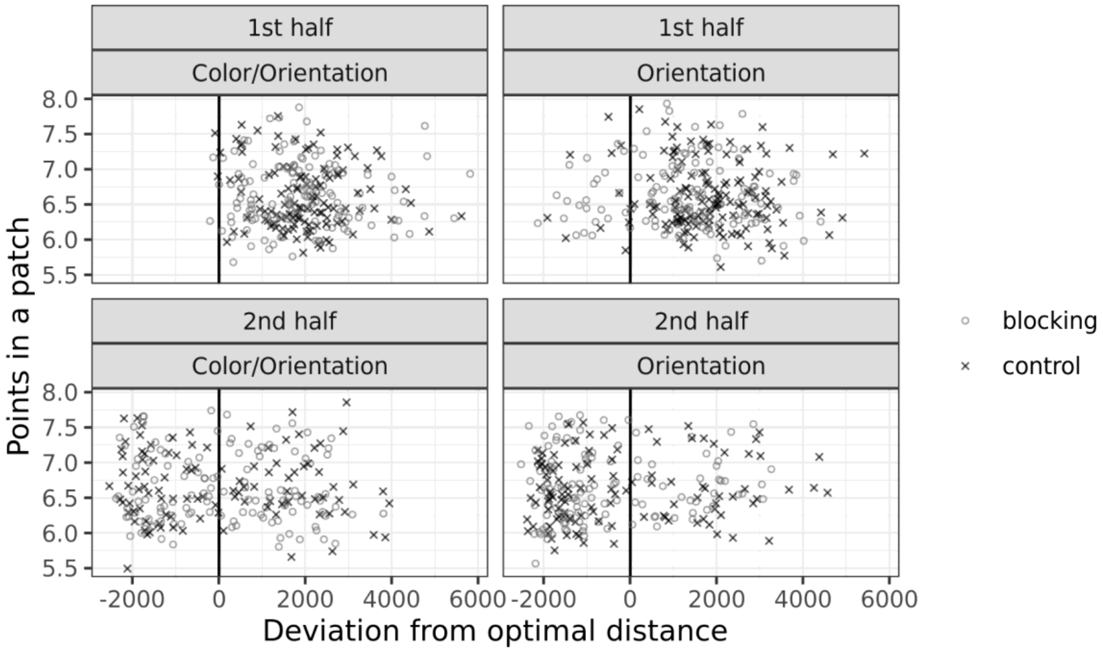


Note. The upper panels showed the first half of each session, and the lower panels showed the second half of each session. The vertical lines represent the optimal search distance.

Figure 11 shows the data from Experiment 1. In Figure 11, the points received in a patch and the deviation from the shortest path length in the color/orientation and orientation sessions are plotted. While the performance did not seem to differ between the control and blocking groups in the color/orientation session, the blocking group in the second half of the orientation session deviated from the shortest value in the negative direction. The mean deviation of each group was -935.55 and -215.68, respectively. As an exploratory analysis, we conducted a Welch's t-test to compare the deviations of the blocking and control groups in the second half of the orientation session. The results showed that the deviation was smaller in the blocking group than in the control group (*t* = 2.83, *df* = 16.70, *p* = .01). As both groups showed negative values, smaller values indicated larger deviations. In

Figure 13

Deviation of the length of actual search paths from the optimal search distance for the color/orientation and orientation sessions in Experiment 3



Note. The upper panels showed the first half of each session, and the lower panels showed the second half of each session. The vertical lines represent the optimal search distance.

the first half of the orientation session, the difference between the groups was not statistically significant (*t* = -1.67, *df* = 11.00, *p* = .12).

Similarly, the points received in a patch and deviation from the shortest path length in the color/orientation and orientation sessions of Experiment 2 are plotted in Figure 12. As an exploratory analysis, we conducted a Welch's t-test to compare the deviations of the blocking and control groups in the second half of the orientation session. In both the first and second halves of the session, there were no statistically significant differences between the deviation values of the blocking and control groups (*t* = -0.79, *df* = 17.99, *p* = .43; *t* = -0.95, *df* = 13.00, *p* = .36).

In Figure 13, the points received in a patch and the deviation from the shortest path length in the color/orientation and orientation sessions of Experiment 3 are plotted. As an exploratory analysis, we conducted a Welch's t-test to compare the deviations of the blocking and control groups in the second half of the orientation session. In both the first and second halves of the session, there were no statistically significant differences between the deviation values of the blocking and control groups (*t* = -1.48, *df* = 38.64, *p* = .15; *t* = -0.98, *df* = 37.87, *p* = .33).

Overall, the deviations from the shortest search distance did not differ between the blocking and control groups when the number of patch-leaves was limited. These results were consistent with the results of the optimal foraging theory reported in the main text. It seems that blocking affected search performance, but some aspects of search were not disrupted. However, the interpretation of these results should be treated carefully, because this analysis only considers the shortest travelling distance and did not consider the optimal search path.

2.5. Discussion: Study 1

In three experiments, we used the visual foraging task to examine the impact of blocking on the process of feature selection and the decision regarding when to transition from the current environment. The features of the stimuli were relevant as cues for reward acquisition. When the number of movements between patches was not limited (Experiment 1), the effect of learning was only observed in reaction times. By contrast, when the number of movements between patches was limited (Experiments 2 and 3), the probability of clicking on a target was lower for participants who learned that the color of the stimuli was a cue in the first phase of the experiment (the blocking group) than for those who did not receive the training in the first phase (the control group). However, upon analyzing the deviation from the optimal leaving time, we found that the effect of blocking was not observed in the decision of when to transition from the current environment. Thus, the findings from the three experiments indicate that blocking influences the selection of target features in visual foraging but does not impact the decision to leave a patch.

The impact of blocking on target selection is also broadly consistent with that of previous studies on blocking human spatial learning. Buckley et al. (2016) demonstrated the blocking of human spatial learning during navigation in a virtual environment. The shape of the search area and the local landmark could both serve as cues to search for a target, but both cues could be blocked. Instead of a spatial learning task, our experiments used a visual foraging task in which cues to search for a target were stimulus features rather than cues in an environment. In the current experiments, we observed that a task-relevant feature during the search was blocked, whereas another task-relevant feature continued to be processed. In the current experiments, participants could select a feature that was not blocked but could not select the blocked feature.

Furthermore, our demonstration of blocking in the visual foraging task extends the blocking phenomenon observed in various contexts and species (Beauchamp et al., 1991; Cheng & Spetch, 2001; Couvillon et al., 2001; Moreyra et al., 2020; Rodrigo et al., 1997; Waelti et al., 2001). The visual foraging task offers a multifaceted approach that allows us to investigate the specific aspects of the task that are disrupted by blocking. Specifically, as we have seen, the visual foraging task used in the current experiments involves two decision-making steps: target selection and patch-leaving decision. Based on our findings, we observed that blocking had a disruptive effect on target selection. When a feature (orientation) was presented in conjunction with an already-learned feature (color), the additional feature (orientation) was blocked. Interestingly, the exploratory analyses with the optimal foraging theory suggest that blocking did not impact the performance of patch-leaving decisions. This implies that learning the task-relevant features of stimuli plays a crucial role in target selection during a foraging search, while patch-leaving decisions are possibly made independently.

Consistent with previous studies conducted using visual foraging tasks that have demonstrated that search is not optimal in certain situations (Kristjánsson et al., 2020; Wolfe, 2013), the current study showed that the actual patch-leaving time deviated from the optimal patch-leaving time. Interestingly, it was not affected by blocking. Although the methods of the analyses could be improved, the findings suggest that the decision on when to leave a patch was based on other criteria, possibly the rate of rewards, and thus was not dependent on the availability of target features.

Therefore, it is likely that such connections exist between the behaviors inside a patch and the patch-leaving behaviors, and learning processes that contribute to these decision-making processes are distinct. Further work is required to explore the interaction between these two aspects of decision-making. There are, at least, two key factors to consider. First, it is necessary to consider the constraints and assumptions of optimal foraging theory before applying it to the current visual foraging task. This study introduced the optimal foraging theory as a novel approach to examine two aspects of decision-making that may be influenced by associative learning. In addition to this, it is vital to consider suitable constraints that accurately represent the limitations of cognitive processes. For example, the analysis with the marginal value theorem did not explore what factors contribute to the deviation from optimal behavior. Therefore, further studies, including computational modeling, are required to determine the precise mechanism of these two aspects of human search behavior.

Secondly, although this study did not measure feature-based attention directly, it is also important to consider our experiments with reference to theories of visual attention. In the current experiments, participants could not select targets with the blocked feature. However, it is unknown whether participants could attend to the blocked feature or not. In the selection history literature, it has been demonstrated that experiences in previous trials can influence attentional guidance in the present trial. For example, reward-predictive features have been shown to bias attention more effectively than features that predict fewer or no rewards (Anderson et al., 2011; Anderson & Halpern, 2017; Bucker & Theeuwes, 2017; Le Pelley et al., 2015; Pearson et al., 2016). The importance of attention has been proposed in theories of associative learning (Esber & Haselgrove, 2011), in which attention is directed towards predictive (Le Pelley, 2010; Mackintosh, 1975) or uncertain stimuli (Pearce & Hall, 1980). If the blocked feature did not convey information about rewards, it is possible that the blocked feature received less attention during learning.

In conclusion, our study provides insights into the phenomenon of blocking in visual foraging tasks. We found that the acquisition of knowledge about one stimulus feature was hindered by the presence of another feature associated with rewards. Furthermore, the decision-making process regarding when to leave the current environment remained unaffected by blocking. These findings expand our understanding of blocking and its impact on target selection and patch-leaving decisions. Theoretical frameworks such as theories of associative learning, feature-based attention, and optimal foraging theory offer explanations for these results. However, to establish a comprehensive framework that can explain search behaviors more broadly, future empirical investigations should focus on exploring the interplay between environmental and cognitive factors that influence decision-making during a search. Such research programs can contribute to a deeper understanding of the complexities of human search behavior and inform the development of more robust models and theories in this field.

3. Study 2

Disrupting Optimal Decision-Making in Visual Foraging: The Impact of Search Experience[3]

3.1. Introduction

Study 1 revealed that both the diet-choice and patch-leaving decisions are involved in the visual foraging task. Hence, it is crucial to directly investigate the diet-choice problem in the context of visual foraging. This entails addressing two key aspects. Firstly, it is essential to manipulate solely the diet-choice component while keeping the patch-leaving component constant, allowing for a focused examination of this specific aspect. Secondly, one potential obstacle to this approach is the inherent uncertainty in human search decisions. For example, when searching for good fruits in the market, fruit color is a good indicator of ripeness; however, it is not a perfect indicator. This inherent uncertainty in the search must be considered when applying a diet choice formulation to a visual search (see 3.2. Theory).

This study aimed to investigate behaviors related to diet choice problems. In the Introduction section, we introduced a traditional diet choice model theorized by Charnov (1976a), which has long been used in the behavioral ecology literature. Next, we demonstrate that an extension of this model, incorporating signal detection theory, can accommodate the uncertainty involved in the diet choice problem during the search. Based on these theoretical considerations, two experiments were conducted to examine whether people optimally modulate their search behaviors in the diet-choice problem. We employed an extension of the task used by Wolfe (2013), in which participants searched for target

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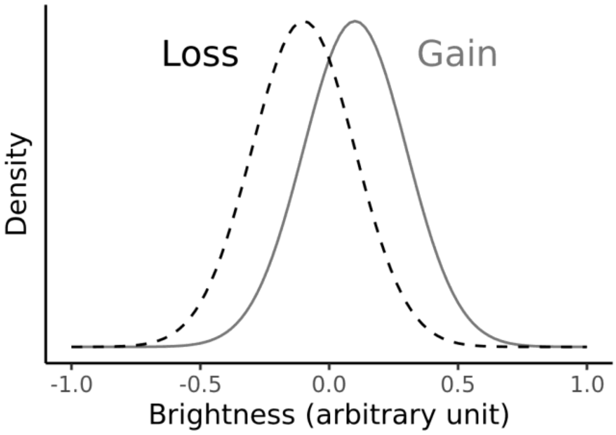
[3] This chapter is based on the paper that has been published as Kobayashi, H., Matsui, H., & Ogawa, H. (2023). Disrupting Optimal Decision-Making in Visual Foraging: The Impact of Search Experience. *Journal of Experimental Psychology: Human Perception and Performance*.

Figure 14

Overlapping distributions of brightness



Note. The two overlapping distributions from which the brightness of the gain stimuli and loss stimuli were sampled respectively.

stimuli to collect points. Participants could gain points by clicking on a good stimulus but lose points when clicking on a bad stimulus. Good and bad stimuli were distinguished based on color brightness, with bright stimuli more likely to be good and dark stimuli more likely to be bad. However, such judgments are imperfect, as even brighter stimuli can sometimes be bad (see Figure 14).

3.2. Theory

3.2.1. Signal-Detection Optimal Diet Model

An assumption of the classical model is that a searcher can discriminate perfectly between each type of stimulus. However, this assumption may not always hold. In many situations, individuals are unable to discriminate stimuli with complete accuracy, which may be due to perceptual ambiguity or a lack of information. For example, when some berries are sweet and others are sour, people may rely on the color of the berries to make their selection. Even though color is a signal of taste that can be reasonably trusted, their choices would still be imperfect because sweet-looking red berries can sometimes be sour, and sour-looking green berries can be sweet. In situations where there is uncertainty in discriminating between types of stimuli, what constitutes optimal behavior?

An answer can be found in the signal-detection optimal diet model (Getty, 1985; Stephens & Krebs, 1986). In this model, we consider only two types of stimuli: gains and losses. To achieve optimal foraging, a searcher should aim to maximize the rate $\frac{\bar{e}}{\bar{h}}$, where $\bar{e}$ represents the average energy gain and $\bar{h}$ represents average time taken. The parameters $\bar{e}$ and $\bar{h}$ are defined as follows:

$$\bar{e} = \frac{l^+}{l^+ + l^-} e^+ \phi^\kappa + \frac{l^+}{l^+ + l^-} e^- \phi \tag{15}$$

$$\bar{h} = \frac{l^+}{l^+ + l^-} h^+ \phi^\kappa + \frac{l^+}{l^+ + l^-} h^- \phi \tag{16}$$

The superscripts $+$ and $-$ indicate gain and loss stimuli, respectively. Parameters that depend on the environment and cannot be manipulated by the searcher are denoted by Roman letters, while parameters that depend on the searcher are denoted by Greek letters. The searcher finds a gain stimulus at a rate l^+ and a bad stimulus at a rate l^-. The time required to search for each type of stimulus is denoted as h^+ and h^-, respectively. Upon capturing a gain or loss stimulus, the searcher gains e^+ and e^-, respectively.

Owing to perceptual ambiguity, the searcher chooses a loss stimulus with a probability of ϕ and a gain stimulus with a probability of ϕ^κ. This model uses a negative-exponential parameterization (Figure 15a) of the signal detection theory (Egan, 1975).

$$\phi = \int_\gamma^\infty \exp(-x)\, dx = \exp(-\gamma) \tag{17}$$

$$\phi^\kappa = \int_\gamma^\infty \exp(-x)\, dx = \exp(-\kappa\gamma) \tag{18}$$

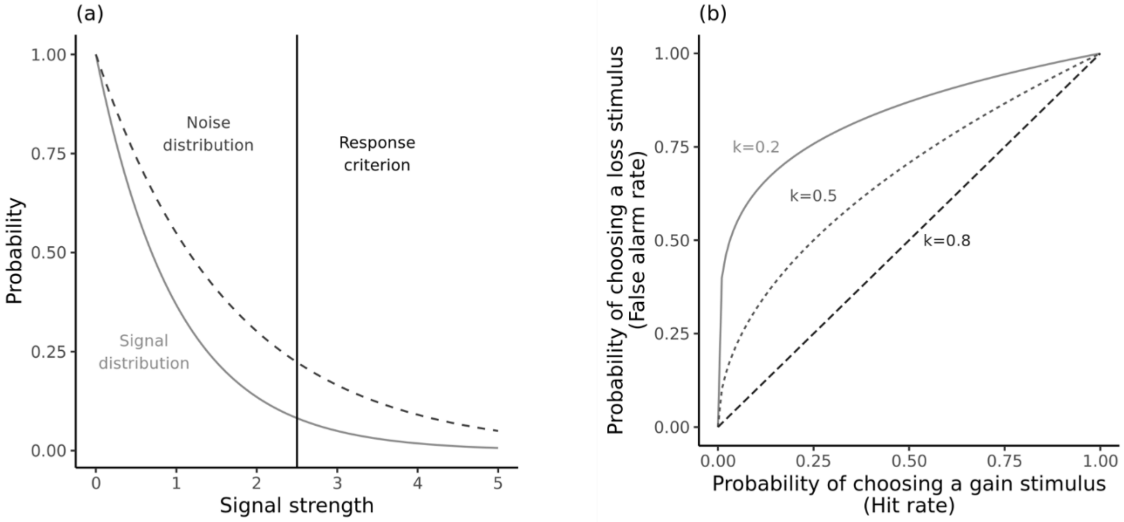
Parameter γ represents the response criterion, whereby a searcher captures a stimulus whenever the level of evidence from a stimulus exceeds this criterion. The parameter κ, ranging from 0 to 1, indicates the discriminability of the searcher between the two types of stimuli. While κ corresponds to d' in the normal parameterization of signal detection theory, it should be noted that these parameters are derived from different assumptions. Specifically, d' represents the distance between the signal and noise distributions, while κ represents the slope of the ROC (receiver operating characteristic) curve. The relationship between ϕ and ϕ^{κ} is depicted in Fig. 15b. When κ is close to 1, the searcher does not discriminate between stimuli. If κ is close to zero, the searcher discriminates between the stimuli well. Getty and Krebs (1985) showed that great tits adjust their foraging behavior in a manner consistent with the predictions of this model.

3.2.2. The Effects of Search History

The signal-detection optimal diet model has three environmental parameters: e (gain), h (handling time), and l (proportion of gain and loss stimuli in the environment). These parameters are determined by either the real-life environment or the experimenter and cannot be controlled by the searcher. By experimentally manipulating these parameters, one can assess whether the model's predictions align with the participants' search behaviors. For instance, in our study, we predicted the response criterion γ when l^+ (proportion of the gain stimuli; Figure 16a) and e^- (loss of capturing a loss stimulus; Figure 16c) were manipulated. Importantly, when a large proportion (>0.8) of gain stimuli is presented, an optimal searcher should adjust the criterion to 0, indicating that they click on

Figure 15

The negative exponential parameterization of signal-detection theory



Note. Noise and signal distributions (a) and the relationship between the probability of choosing a gain stimulus and a loss stimulus depending on the values of $\boldsymbol{\kappa}$ (b). The hit and false-alarm rates can be calculated by measuring the area under the curve between 0 and the response criterion c. The parameter $\boldsymbol{\kappa}$, where $\mathbf{0} < \boldsymbol{\kappa} < \mathbf{1}$, determines the relationship between the hit and false-alarm rates. When $\boldsymbol{\kappa} = \mathbf{1}$, the ROC function becomes a straight line, representing chance performance.

stimuli regardless of the evidence received. In other words, a certain degree of selection of bad stimuli should be tolerated to achieve optimal performance.

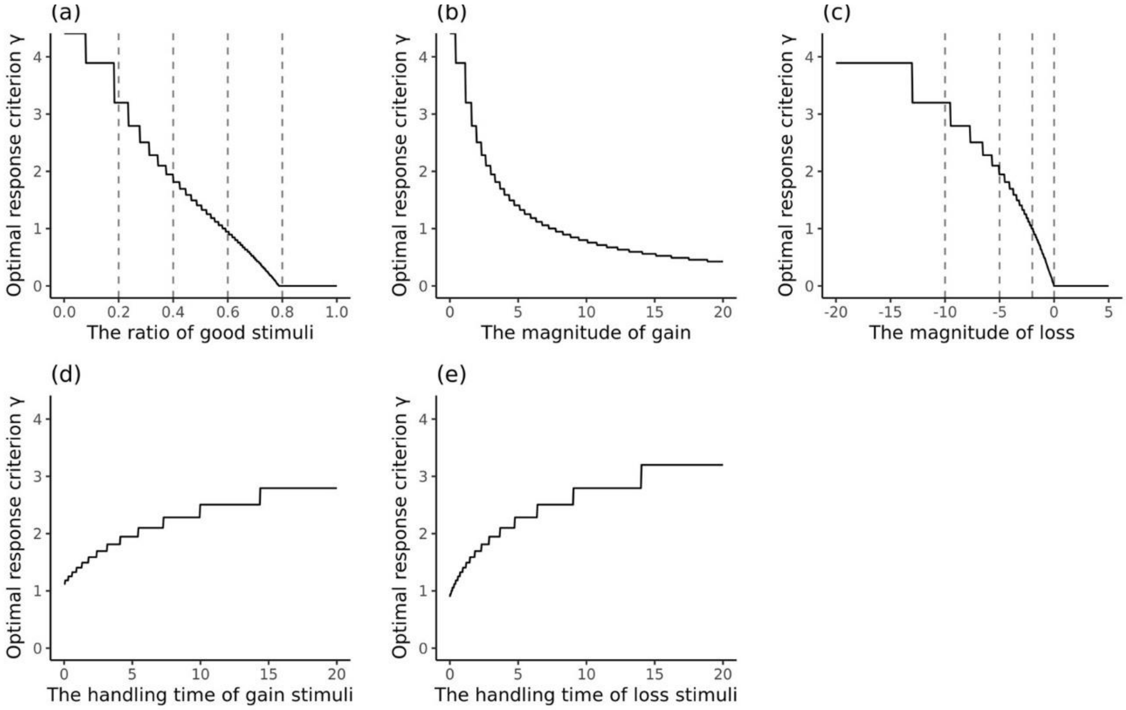
However, it remains unclear whether individuals adjust their behavior as predicted by the model. Previous studies have indicated that search performance can be influenced by search history. For instance, Fougnie et al. (2015) demonstrated that performance in a visual foraging task varied when the proportion of gain stimuli was manipulated. While their study focused on the patch-leaving problem, the results imply that visual foraging performance is influenced by the environment encountered by the searchers. Extensive research on traditional visual search tasks has also emphasized the significance of search history as a factor related to search performance (Anderson et al., 2021; Awh et al., 2012). Thus, search history may constitute a crucial factor that influences performance adjustment in diet-choice problems.

We compared the prediction by the model and the performance of the participants by manipulating two environmental parameters: the ratio of gain stimuli (l^{+}) in Experiment 1, and the magnitude of the loss associated with clicking loss stimuli (e^{-}). In addition, we systematically varied these parameters across the phases of the eight search displays. In one extreme scenario, an optimal searcher would accept all stimuli regardless of their quality (indicated by the right-hand dashed lines in Figure 16a and 16c). One group of participants experienced the “falling” condition, in which the environment gradually became less profitable. The other group experienced a “rising” condition, in which the environment gradually became profitable.

We conducted preliminary simulations (Figure 16) to guide our selection of parameters. These simulations involved calculating the optimal search efficiency (R^*) and the corresponding optimal response criterion (γ^*) when the search efficiency was maximized. To achieve this, we systematically varied the false-alarm rate (ranging from 0 to 1 in increments of 0.01), the ratio of gain stimuli (ranging from 0 to 1 in increments of 0.01), the magnitude of gain stimuli (ranging from 0 to

Figure 16

The optimal response criteria predicted by the signal-detection optimal diet model



Note. The results of simulations conducted with the signal-detection optimal diet model. The solid lines indicate the optimal response criteria. Each figure represents the optimal response criterion under different conditions: (a) when the ratio of gain stimuli changes, (b) when the magnitude of gain changes, (c) when the magnitude of loss changes, (d) when the handling time of gain stimuli changes, and (e) when the handling time of loss stimuli changes. Figures 16a and 16c display dotted vertical lines at the parameter values used in our experiments.

20 in increments of 0.04), the magnitude of loss stimuli (ranging from -20 to 5 in increments of 0.05), and the handling time of gain and loss stimuli (ranging from 0 to 20 in increments of 0.04), respectively. We identified the ratio of gain stimuli and the magnitude of loss stimuli as the parameters to be manipulated in our experimental design. Our simulations revealed that altering either of these parameters had the most pronounced impact on participants' behavior. To determine the specific values for experimental manipulation, we visually examined the simulated R^* values and identified the ratios at which significant changes occurred. Based on this analysis, we selected the ratios of 0.2, 0.4, 0.6, and 0.8 for implementation in Experiment 1. These values were chosen to effectively capture the range of potential influences on participant decision-making processes. The same procedure was used to determine the size of the losses in Experiment 2.

3.3. Experiment 1

3.3.1. Methods

3.3.1.1. Participants

A total of 23 students (mean age = 18.90 years, range 18-21; 20 females, 3 males, 0 diverse), all of whom were Japanese, participated in the experiment for partial fulfillment of course credit. Data were collected in 2022. We allocated a 2-week period for applications to participate in the study, and as a result, 23 people enrolled as participants. All participants provided written informed consent and reported normal or corrected-to-normal vision. None of the participants were aware of the purpose of the study. Ethical approval was obtained from the Kwansei Gakuin University Committee for Regulations for Behavioral Research with Human Participants.

3.3.1.2. Apparatus

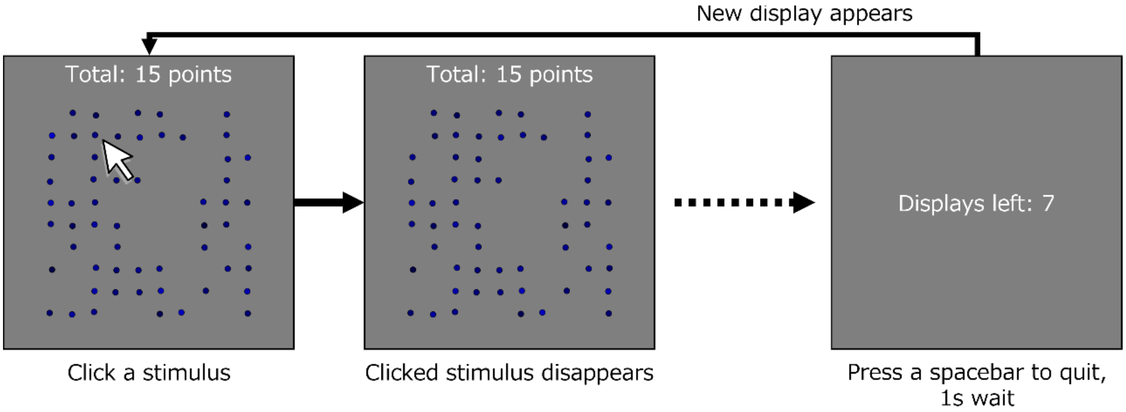
All the experimental sessions were conducted in a dimly lit room. The experimental stimuli were presented on a 24.5-inch display at a refresh rate of 60 Hz (ROG PG258Q; ASUS). The experiments were programmed and controlled using PsychoPy (version 2020.2.1; Peirce et al., 2019). The responses were collected using a mouse (G-Tune Optical Gaming Mouse GTCL0880BK1, Mouse Computer). The viewing distance was approximately 65 cm and a chin rest was not used to maintain this distance.

3.3.1.3. Procedure

Participants completed four sessions of the visual foraging task. Each session consisted of eight search displays (Figure 17). At the beginning of each session, a search display was presented with 56, 58, or 60 stimuli on a grey background. The number of stimuli on the search display was randomly determined at the start of each session. Participants used a mouse to click on one of the stimuli. Some stimuli were "gain" stimuli; participants scored five points by clicking on them. The other stimuli were "loss" stimuli; participants lost three points by clicking on them. The clicked stimuli disappeared immediately. The sum of the points acquired by the participants is shown on the upper left side of the display. This information was updated every time the participants clicked on a stimulus.

Figure 17

A schematic illustration of a trial



Note. Participants acquired or lost points depending on whether they clicked on a gain or loss stimulus. Participants could quit a search by pressing a space bar.

The participants clicked as many stimuli as they wanted until they pressed a space bar on the keyboard to complete the search. When the participants pressed the spacebar, the search display was replaced with a screen that told them the number of screens remaining in the session. This screen lasted 1000 ms and was then replaced by a new search display. The points acquired on one display did not carry over to the next display. This procedure is implemented to ensure that the selection of targets remains independent of the patch-leaving decisions. The session ended automatically after eight search displays were presented. Between sessions, the participants rested for a minute. The participants were explicitly informed that they had eight displays to complete within one block, and the number of remaining displays in a block was shown on the screen during the rest period. After resting, a screen appeared to prompt participants to start a new session by pressing a space bar. The experiment lasted for approximately 40 min.

Each stimulus was blue and varied in brightness. The brightness of the gain and loss stimuli were sampled from two normal distributions. The distribution for the gain stimuli had a mean of 0.1 and a variance of 0.2; the distribution for the loss stimuli had a mean of -0.1 and a variance of 0.2. Thus, these two distributions overlapped (Figure 14). The distance of the two overlapping distributions was 1.0, calculated as (0.1 - (-0.1)) / 0.2. Through this manipulation, we intended to introduce uncertainty in distinguishing gain from loss, through brighter stimuli tend to be obtained, there is always some degree of uncertainty.

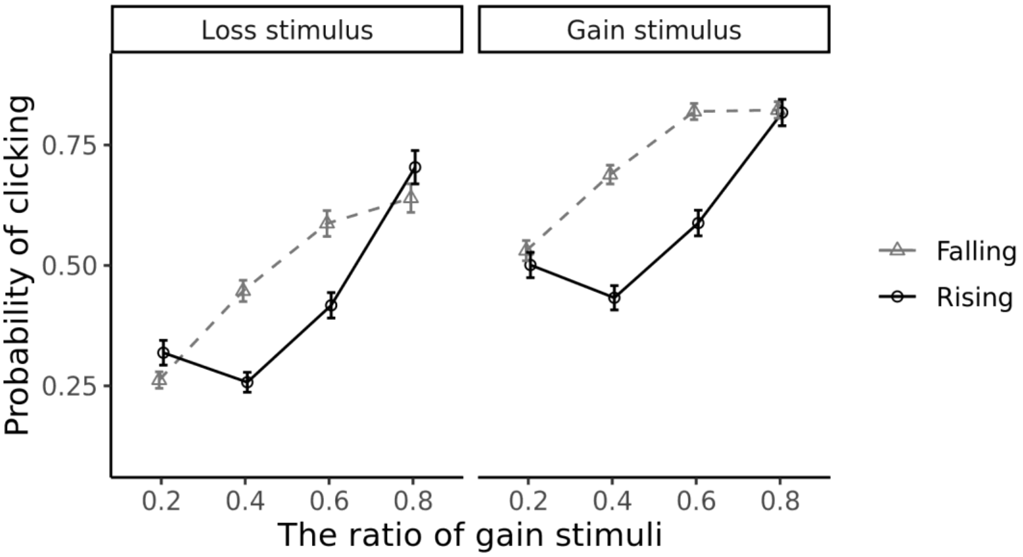
The ratio of gain stimuli to loss stimuli varied across sessions. The ratios used in the experiments were 0.8, 0.6, 0.4, and 0.2. The ratios were determined according to the results of the simulations using the signal-detection optimal diet model (Figure 16). Eleven participants were allocated to the rising group, while the remaining 12 participants were assigned to the falling group. The sessions proceeded in the following order:0.4, 0.6, and 0.8. In contrast, participants in the “falling” group completed four sessions in reverse order; the ratio of the first session was 0.8, and the ratio of the last session was 0.2. The participants were not informed of the ratio of gain and loss stimuli or their changes before the experiment.

3.3.2. Results

We performed a series of Bayesian model-based analyses to investigate whether the participants adjusted their behaviors according to changes in the environment. First, we estimated each participant's discriminability κ_{subj} and response criterion $\gamma_{subj,phase}$ from the data using the power-law signal detection model. Figure 18 shows the probability of clicking on loss or gain stimuli. We assumed that the discriminability κ_{subj} was fixed across sessions, and the response criterion $\gamma_{subj,phase}$ was sampled from different distributions across sessions. The discriminability κ_{subj} and

Figure 18

The probability of clicking on loss and gain stimuli in Experiment 1



Note. The figure shows the probability of clicking on loss and gain stimuli on each patch in Experiment 1, which is calculated as the number of clicks divided by the number of stimuli. The solid and dotted lines represent the falling and rising groups respectively. The error bars represent the standard errors.

the response criteria $\gamma_{subj,phase}$ are the parameters of interest. To assess whether the response criteria were adjusted based on changes in the environment, we compared models that assumed adjustments in the response criteria and those that assumed no adjustments by calculating the Bayes factors. We used a hierarchical modeling approach and assumed that these individual parameters of κ_{subj} and $\gamma_{subj,phase}$ were sampled from the hyperparameters μ_κ and μ_γ, respectively. The participant's clicking behavior on loss and gain stimuli on each display, $Loss_{subj,phase,patch}$ and $Gain_{subj,phase,patch}$, respectively, is modeled using binomial distributions with the number of trials as $N_{loss_{subj,phase,patch}}$ and $N_{gain_{subj,phase,patch}}$ and the probability of clicking on loss and gain stimuli as $\theta_{loss_{subj,trial}}$ and $\theta_{gain_{subj,trial}}$. The model specifications are as follows:

$$\mu_\gamma \sim \mathrm{Normal}(0,5)$$

$$\mu_\kappa \sim \mathrm{Normal}(0,5)$$

$$\sigma_\gamma \sim \mathrm{LogNormal}(0,1)$$

$$\sigma_\kappa \sim \mathrm{LogNormal}(0,1)$$

$$\gamma_{subj,session} \sim \mathrm{Normal}(\mu_\gamma, \sigma_\gamma)$$

$$\kappa_{subj} \sim \mathrm{Normal}(\mu_\kappa, \sigma_\kappa)$$

$$\theta_{f_{subj,trial}} = \exp(-\gamma_{subj,session})$$

$$\theta_{h_{subj,trial}} = \theta_{f_{subj,session}}^{k_{subj}}$$

$$Loss_{subj,session,display} \sim \mathrm{Binomial}(N_{loss_{subj,session,display}}, \theta_{f_{subj,session}})$$

$$Gain_{subj,session,display} \sim \mathrm{Binomial}(N_{gain_{subj,session,display}}, \theta_{h_{subj,session}})$$

(19)

We used R (version 4.1.0) for all the analyses. For Bayesian modeling, we coded the models using the probabilistic programming language Stan (Stan Development Team, 2022). We used the CmdStanR package (Stan Development Team, 2021) as the R interface for Stan to obtain Markov chain Monte Carlo (MCMC) samples. We sampled ten independent chains over 3,000 iterations. To ensure that each chain converged to a stationary distribution, the first 1000 samples from each chain were discarded as warm-up samples. We confirmed that all chains converged when all $\hat{R}$ values were less than 1.004. The Bridgesampling package (Gronau et al., 2020) was used to calculate the Bayes factors.

Changes of Response Criteria between Sessions

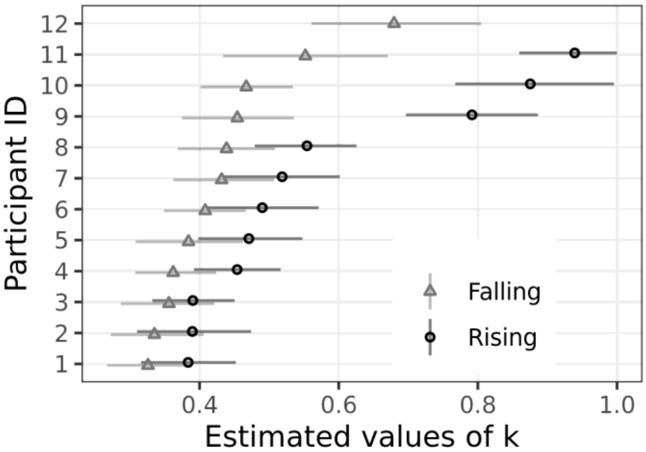
Overall, participants in both groups seemed to discriminate gain from loss stimuli reasonably well based on their colors. The estimated values of the discriminability κ_{subj} are shown in Figure 19. Although three participants in the falling group showed extremely low levels of discriminability, there was no systematic difference in discriminability between the groups.

To assess whether participants adjusted the response criteria based on changes in the environment, we compared the model assuming a difference between all conditions (full model) and the model assuming no difference (null model) for the falling and rising groups. The full model assumes that participants establish their response criteria for each session based on the estimated distributions that vary across sessions. This can be formalized as follows:

$$\mu_{\gamma_{session}} \sim \mathrm{Normal}(0,5)$$

Figure 19

Estimated values of discriminability $\boldsymbol{\kappa_{subj}}$ for falling and rising displays in Experiment 1



$$\sigma_{\gamma_{session}} \sim \text{LogNormal}(0,1)$$

$$\gamma_{subj,session} \sim \text{Normal}(\mu_{\gamma_{session}}, \sigma_{\gamma_{session}})$$

(20)

On the other hand, the null model assumes that participants establish their response criteria for each session based on the estimated distributions that are the same across sessions. This can be formalized as follows:

$$\mu_{\gamma} \sim \text{Normal}(0,5)$$

$$\sigma_{\gamma} \sim \text{LogNormal}(0,1)$$

$$\gamma_{subj} \sim \text{Normal}(\mu_{\gamma}, \sigma_{\gamma})$$

(21)

In both groups, the full models provided a better fit for the data than null models (BFs > 10^{48}). This suggests that the response criteria were adjusted based on changes in the ratio of gain stimuli in the environment.

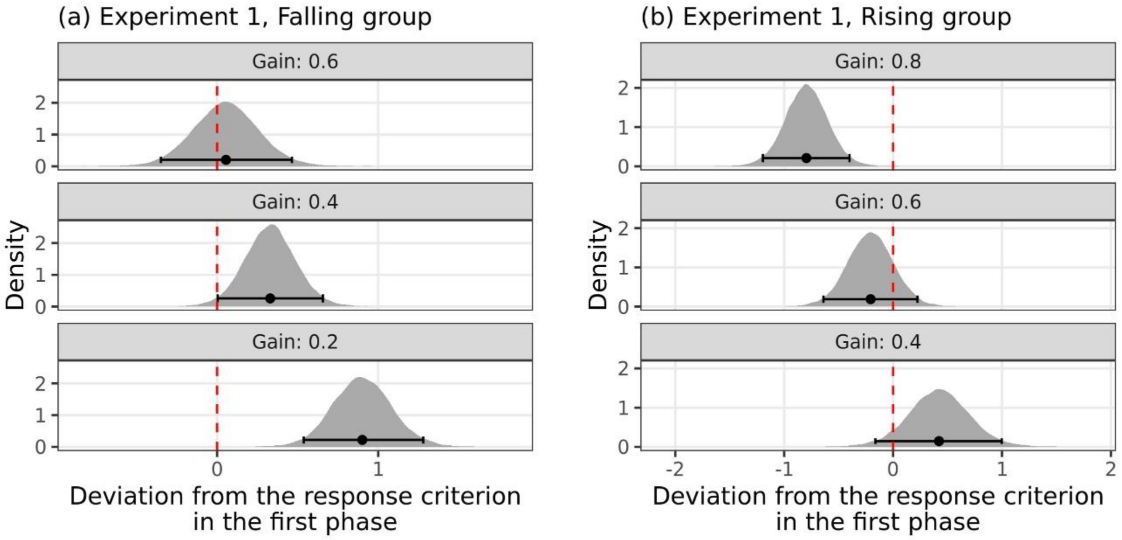
Next, we examined the effect of the order by comparing the response criteria. To facilitate comparison, we created a model where the response criterion for each session is calculated by adding an offset to the response criterion of the first session. For example, in the rising group, we calculated the difference between the response criterion in the 0.8 session and the response criterion in the 0.2 session by adding the offset to the response criterion in the 0.2 session. The results are shown in Figure 20. The error bars represent the 95% credible intervals. If the credible intervals do not include zero, we conclude that there is a difference between the response criteria of a specific session and the first session. In the falling group (Figure 20a), where participants began from the 0.8 session, the response criterion in the 0.2 session was higher than that in the 0.8 session. In the rising group (Figure 20b), where participants began from the 0.2 session, the response criterion in the 0.8 session was higher than that in the 0.2 session. These findings indicate that performance adjustment was observed only in the final session for both the rising and falling groups.

Deviations from the Optimal Response Criteria

To assess whether participants adjusted their performance optimally based on the changes in the environment, we calculated the optimal response criterion $\gamma^*_{subj,phase}$ for each participant in each session based on the estimated values of κ_{subj}, and compared them to the estimated values of $\gamma_{subj,phase}$. If the participants adjusted their performance optimally, their individual response criteria would not deviate from the optimal criterion $\gamma^*_{subj,phase}$. We defined the performance as a deviation from the optimal value when the 95% highest density intervals (HDIs) of the difference between the estimated and optimal values were above or below 0. By contrast, if the participants' search was suboptimal, their individual response criteria deviated from the optimal criterion. For conservative

Figure 20

Differences from the response criterion in the first session: Experiment 1



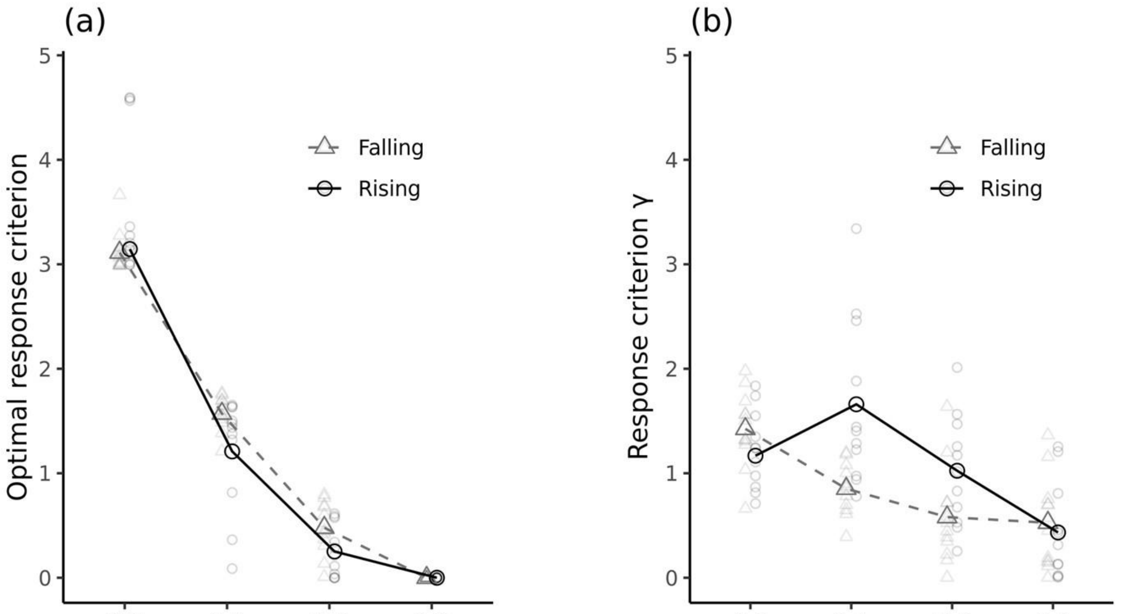
Note. Differences from the response criterion in the 0.8 session in the falling group (a) and differences from the response criterion in the 0.2 session in the rising group (b).

responses, the individual response criteria $\gamma_{subj,phase}$ would be smaller than the optimal criterion $\gamma^{*}_{subj,phase}$; on the other hand, for liberal responses, the individual response criteria $\gamma_{subj,phase}$ would be larger than the optimal criterion $\gamma^{*}_{subj,phase}$. Additionally, we compared the response criteria of each participant between phases to assess whether performance was modulated as the environment changed.

The mean values and individual estimations of the optimal response criteria $\gamma^{*}_{subj,phase}$ are shown in Figure 21a, and the actual response criteria of each participant are shown in Figure 21b. Note that compared to the optimal response criteria in an environment where the ratio of gain stimuli was

Figure 21

Values of response criterion calculated in Experiment 1



Note. Optimal values of response criterion $\boldsymbol{\gamma}^{*}_{subj}$ calculated from the signal-detection optimal diet model and *discriminability* $\boldsymbol{\kappa}_{subj}$ of each participant (a) and actual values of response criterion $\boldsymbol{\gamma}^{\square}_{subj}$ (b).

large (0.8) or small (0.2), the actual response criteria were too conservative and liberal, respectively. When the ratio of gain stimuli on a display is large (0.8), the optimal performance would be to click on all stimuli, regardless of whether they are gain or loss stimuli. In contrast, in a display where the ratio of gain stimuli is small (0.2), the optimal performance would be to click only on stimuli that clearly have target features. Although the changes in the actual optimal criteria followed the pattern observed in the optimal response criteria, the performance deviated from optimality.

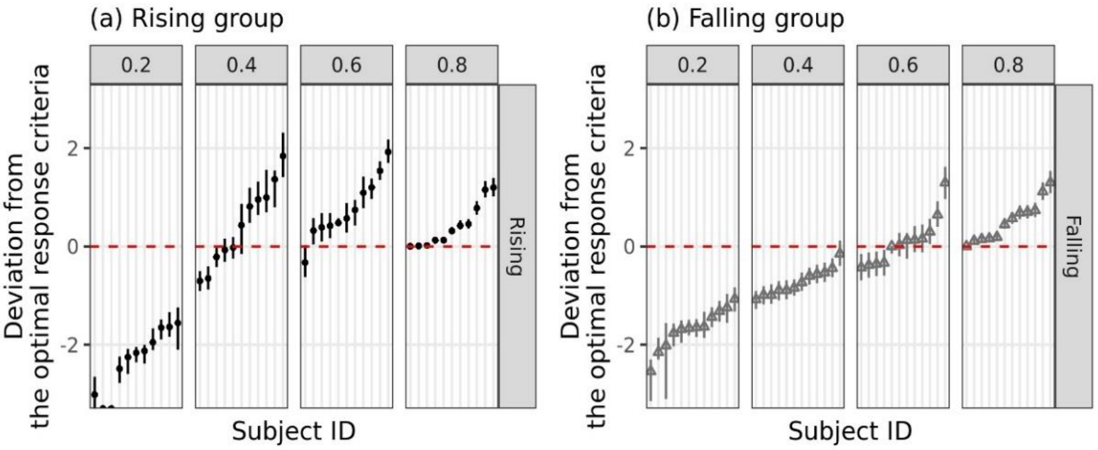
Figure 22 shows deviations of the individual response criterion $\gamma_{subj,phase}$ from the optimal value for each participant. The response criteria in the 0.2 session deviate largely from the optimal response criteria. The 95% HDIs of participants' deviations of $\gamma_{subj,phase}$ were all below 0. This showed that participants' response criteria were too liberal compared to the optimal criteria in both the falling and rising groups. In contrast, the response criteria in the 0.8 session were larger than the optimal value. The 95% HDIs of all participants were above 0 (the HDIs of the participants with the smallest value of $c_{subj,phase}$ were [0.054×10^{-4}, 0.009], which were above 0), indicating that their performance was too conservative compared to the optimal response criteria.

Performances in the 0.4 and 0.6 sessions differed between the rising and falling groups. On the one

hand, the rising group deviated from the optimal response criteria in the 0.6 session, with only one participant's HDI overlapping 0 ([-0.637, 0.039]) and the HDIs of the remaining participants being above 0. In other words, the response criteria were higher than the optimal response criteria in the 0.6 session of the rising group. However, the falling group deviated from the optimal response

Figure 22

The deviations from the optimal values $\gamma^*_{subj,phase}$



Note. The error bars are 95% highest density intervals (HDIs).

criteria in the 0.4 session, with the HDI of only one participant overlapping 0 ([-0.399, 0.080]), and the HDIs of the remaining participants were below 0. This means that the response criteria were lower than the optimal response criteria in the 0.4 session of the falling group. In summary, whereas the falling group performed too liberally in the 0.4 session, the rising group performed too conservatively in the 0.6 session. These deviations appeared in the third session for each group, suggesting that the response criteria were not properly adjusted between the second and third sessions.

3.3.3. Discussion

In Experiment 1, we assessed whether participants adjusted their response criteria according to the environment, as predicted by the model. For this purpose, we manipulated one of the parameters (l_g, the proportion of gain stimuli in the environment) included in the signal-detection optimal diet model. Both groups modulated their response criteria based on changes in the proportion of gain stimuli in the environment; however, the adjustment was not optimal. When the optimal response criterion was extremely conservative or liberal, participants tended to adopt suboptimal strategies.

When the ratio of gain stimuli in the environment was 0.8, the optimal strategy was to take risks by clicking on all the available stimuli. By contrast, when the ratio was 0.2, the optimal strategy was to avoid risks by clicking on fewer stimuli. In both situations, participants in the rising and falling groups could not adopt these strategies and adopted more conservative (0.8 sessions) or liberal (0.2 sessions) response criteria.

Performance in the intermediate sessions was also suboptimal, where the environment was moderately profitable or unprofitable, depending on the order in which the participants experienced the environment. In the rising group, the response criteria in the 0.6 session should have been more liberal if the optimal response criteria were adopted. This suggests that the response criteria were influenced by the preceding environment (the 0.4 session), where the participants used more conservative response criteria. Similarly, in the falling group, the response criteria in the 0.4 session should have been more conservative; however, the actual response criteria were higher. This also suggests that the preceding environment (0.6 session), where more liberal criteria were optimal, influenced the performance.

In our experiment, all stimuli were presented simultaneously. Despite this setup potentially facilitating efficient observation of environmental information and learning, we still observed a similar pattern of results. This finding suggests that past experiences in the environment influenced behavior in the current environment, resulting in a delayed adjustment of response criteria. Moreover, a change between sessions was observed in the final session for both the rising and falling groups, aligning with the findings of a prior study on great tits (Getty & Krebs, 1985). This experiment revealed a time lag between environment changes and corresponding performance modulation. In their study, a similar task was employed, where stimuli were presented individually to the birds, making direct observation impossible. Consequently, the birds could only infer changes through interactions with the environment. Inaccurate inference or delays in the inference process could disrupt performance adjustments. If this inference-based explanation holds, increased experience in the environment could lead to enhanced performance. To explore this, designing an experiment featuring a greater number of displays per session is feasible.

In summary, our findings indicate that while our experimental setup facilitated efficient information observation and learning, similar delayed adjustment patterns emerged as in situations where individual stimulus presentation limited direct observation. This implies that past environmental experiences continue to influence behavior in the current context, leading to delayed response criterion adjustments.

3.4. Experiment 2

3.4.1. Methods

3.4.1.1. Participants

A total of 26 students (mean age = 19.17 years, range 18-22; 20 females, 6 males, 0 diverse), all of whom are Japanese, participated in the experiment for partial fulfillment of course credit. Data were collected in 2022. We allocated a two-week period for applications to participate in the study. As a result, 26 people enrolled as participants. Among them, three people failed to finish the task during the allocated timeslot of 65 minutes, and the data of these participants were not included in the following analyses. Additionally, a part of the data was not recorded for two participants, and the data of these participants were also not included in the following analyses. Accordingly, the following analyses were based on the valid data from 21 participants. All participants provided written informed consent and reported normal or corrected-to-normal vision. None of the participants was aware of the purpose of the study or participated in Experiment 1. Ethical approval was obtained from the Kwansei Gakuin University Committee for Regulations for Behavioral Research with Human Participants.

3.4.1.2. Apparatus

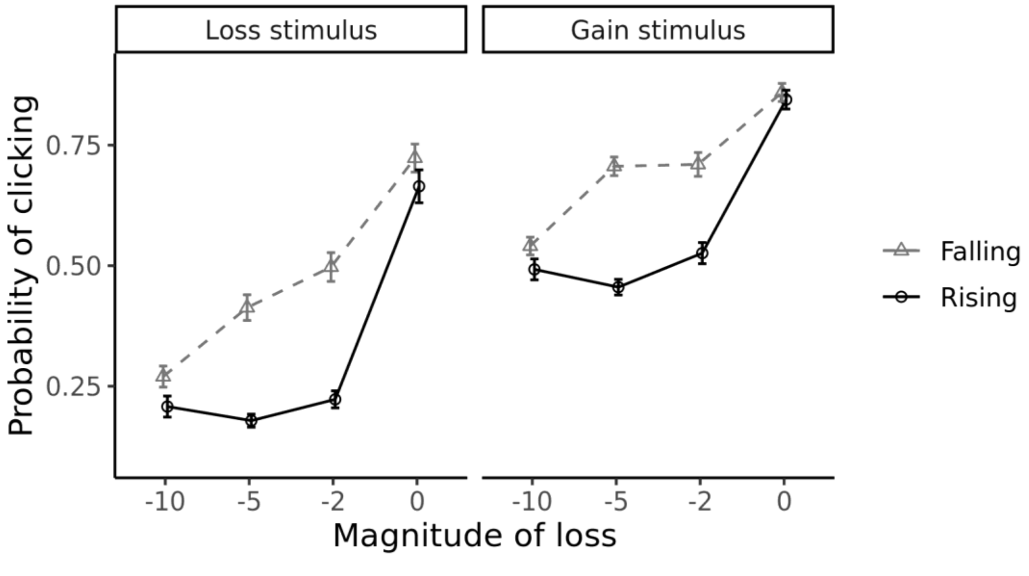
The same apparatus used as in Experiment 1.

3.4.1.3. Procedure

Participants completed four sessions of the visual foraging task. As in Experiment 1, both gain and loss stimuli were presented on a search display. Participants scored five points by clicking on the gain stimuli. When the participants clicked on the loss stimuli, they lost 0, 2, 5, or 10 points. The amount of loss was changed in each session to investigate the influence of search history. Participants were divided either into "rising" or "falling" groups. Eleven participants were allocated to the rising

Figure 23

The probability of clicking on loss and gain stimuli in Experiment 2



Note. The figure shows the probability of clicking on loss and gain stimuli on each patch in Experiment 2, which is calculated as the number of clicks divided by the number of stimuli. The solid and dotted lines represent the falling and rising groups respectively. The error bars represent the standard errors.

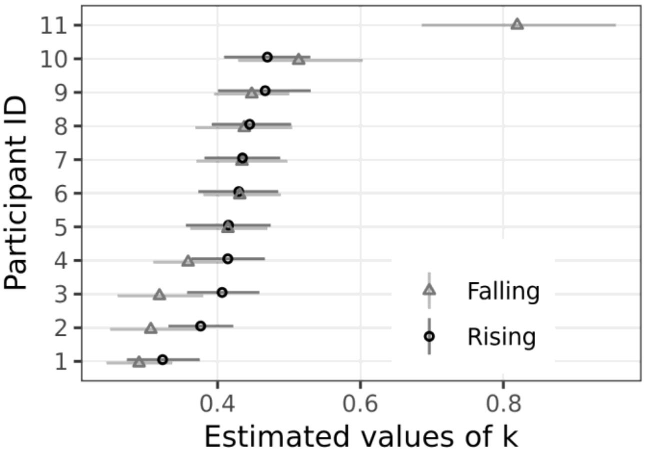
group, while the remaining 12 participants were assigned to the falling group. Participants in the rising group searched in the first session with a loss of -10 points. Subsequently, the sessions proceeded in the following decreasing order: -5, -2, and 0 points. Participants in the falling group completed four sessions in reverse order: the amount of loss in the first session was 0 points, and the amount of loss in the last session was 10 points. The ratio of the gain to loss stimuli in this experiment was always 1 (Gain):1 (loss).

3.4.2. Results

The procedures used for the analyses were similar to those in Experiment 1. Figure 23 shows the probability of clicking on loss or gain stimuli. Figure 24 shows the estimated values of the discriminability κ_{subj}. Although one participant in the fall group showed a low level of discriminability, there was no systematic difference in the discriminability of each participant between groups. As in Experiment 1, participants in both groups seemed to discriminate gain from loss stimuli reasonably well based on their colors.

Figure 24

Estimated values of discriminability κ_{subj} *for falling and rising displays in Experiment 2*



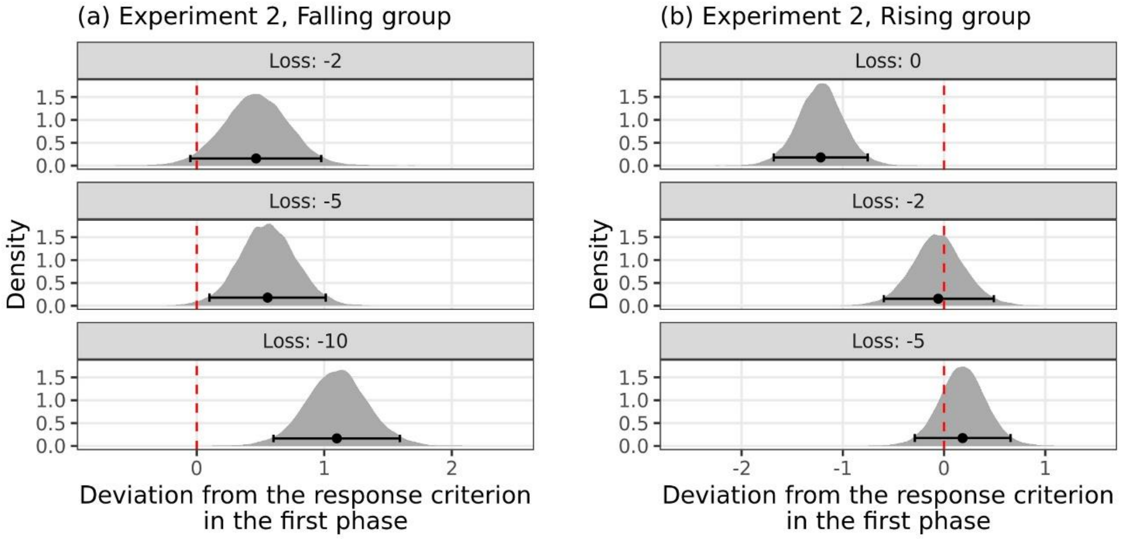
3.4.2.1. Changes of Response Criteria between Sessions

As in Experiment 1, to assess whether participants adjusted the response criteria based on environmental changes, we compared the model assuming a difference between all conditions (full model) and the model assuming no difference (null model) for the falling and rising groups, respectively. In both groups, the full models provided a better fit for the data than the null models (BFs $> 10^{55}$). This suggests that the response criteria were adjusted based on changes in the extent of environmental loss.

Next, we examined the effect of the order by comparing the response criteria. As in Experiment 1, we created a model where the response criterion for each session is calculated by adding an offset to the response criterion of the first session. The results are shown in Figure 25. The error bars represent the 95% credible intervals. In the falling group (Figure 25a), where participants began

Figure 25

Differences from the response criterion in the first session: Experiment 1



Note. Differences from the response criterion in the 0.8 session in the falling group (a) and differences from the response criterion in the 0.2 session in the rising group (b).

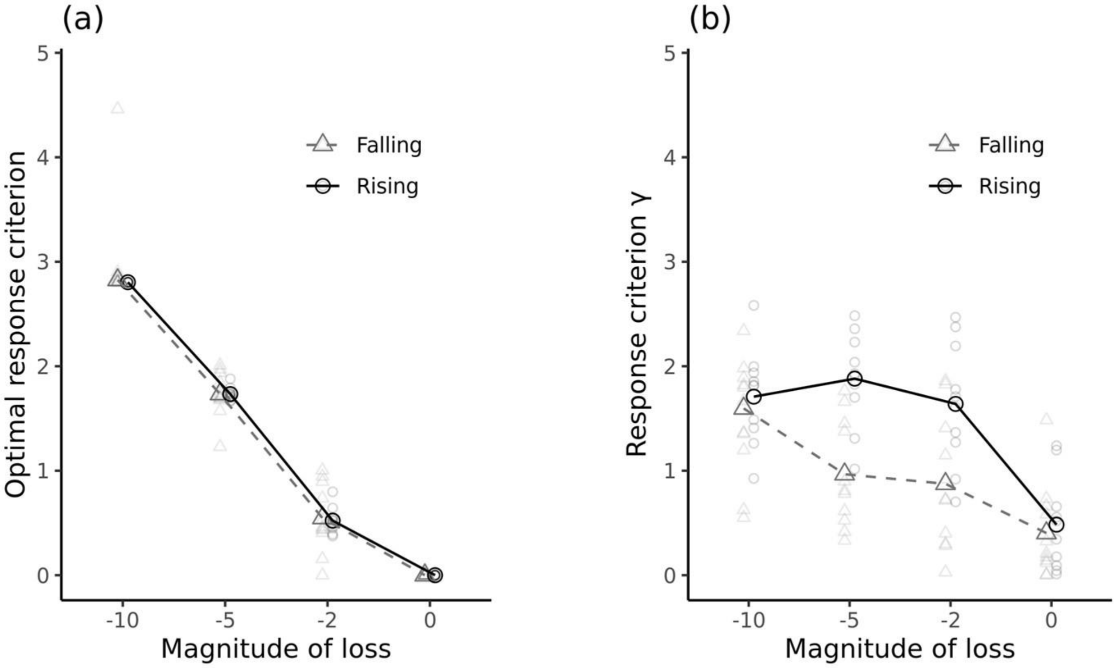
from the 0-point loss session, the response criteria in the 5- and 10-point loss sessions were higher than that in the 0-point loss session. In the rising group (Figure 25b), where participants began from the 10-point loss session, the response criterion in the 0-point loss session was higher than that in the 10-point loss session. These findings suggest that performance adjustment occurred earlier in the falling group compared to the rising group, where the adjustment was only observed in the final session.

3.4.2.2. Deviations from the Optimal Response Criteria

To assess whether the participants optimally adjusted their performance, we calculated the optimal response criteria and deviations of the actual performance from the optimal value for each participant in each session. The mean values and individual estimations of the optimal response criteria $\gamma^{*}_{subj,phase}$ are shown in Figure 26a, and the actual response criteria of each participant are shown in Figure 26b. When the cost of loss stimuli was 0, the optimal response criterion was 0, which meant that clicking on all stimuli resulted in optimal performance. In contrast, the cost of loss stimuli was large (-10), and the optimal response criterion was high and conservative, which means that participants could click a stimulus only when they were confident that the stimulus was a gain stimulus.

Figure 26

Values of response criterion calculated in Experiment 2



Note. Optimal values of response criterion $\boldsymbol{\gamma}^{*}_{\boldsymbol{subj}}$ calculated from the signal-detection optimal diet model and discriminability $\boldsymbol{\kappa_{subj}}$ of each participant (a) and actual values of response criterion $\boldsymbol{\gamma_{subj}}$ (b).

Otherwise, clicking as little as possible is considered optimal. As in Experiment 1, the response criteria changed with the environment; however, the adjustment was apparently suboptimal.

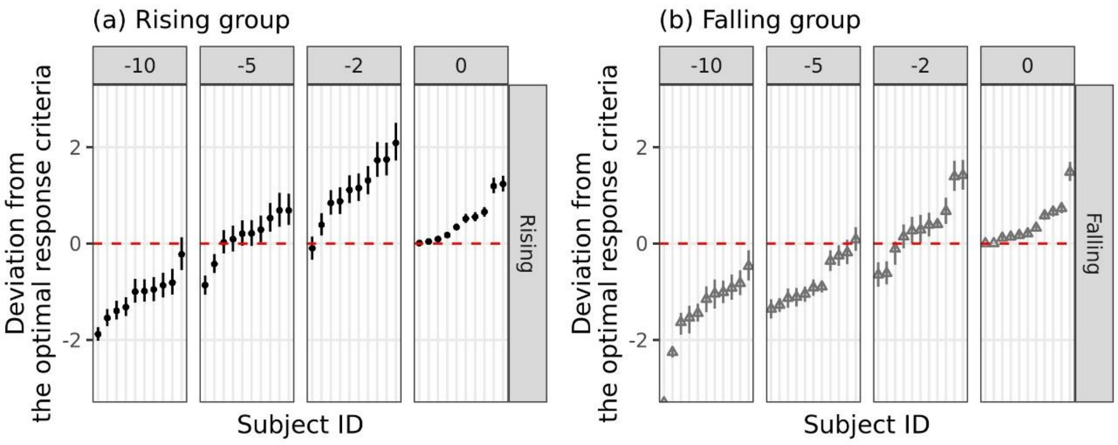
Performance in an environment without loss (0-point loss session) was too conservative compared to the optimal response criterion, whereas performance in an environment with a large loss was too liberal. Figure 27 shows the deviations from the optimal values for each participant. The response criterion for the 10-point loss session deviated significantly from the optimal response criterion. In the rising group, the 95% HDIs were below zero, except for one participant ([-0.559, 0.113]). The 95% HDIs of deviations of $\gamma_{subj,phase}$ of participants in the falling group were all below

0. This showed that the response criteria of the participants were too liberal compared to the optimal criteria in both the falling and rising groups. By contrast, the response criteria in the 0-point session were higher than the optimal values. The 95% HDIs of all participants were above 0 (the HDIs of the participants with the smallest value of $c_{subj,phase}$ were [0.001×10^{-4}, 0.007], which were above 0), indicating that their performance was too conservative compared to the optimal response criteria.

Performance in the 2 and 5-point loss sessions differed between the rising and falling groups. In the 2-point loss session, 95% of the HDIs of the participants in the rising group were above 0, except for one participant ([-0.333, 0.151]), whereas the 95% of the HDIs of four out of 11 participants in the falling group were above 0, and the HDIs of two participants were below 0. This indicates that the response criteria were higher than the optimal response criteria in the 2-point loss session for the rising group, suggesting that their performance of the rising group was comparatively liberal in the 2-point loss session. However, this trend was not observed in the fall group. In the 5-point loss session, the 95% HDIs of 9 out of 11 participants in the falling group were below 0, whereas the 95% HDIs of only 2 out of 10 participants in the rising group were above 0, and the HDIs of four participants were below 0. This means that the response criteria were lower than the optimal response criteria in the 5-point loss session of the falling group, suggesting that the performance of the falling group was conservative in the 5-point loss session. The performance of the rising group did not exhibit this tendency. In summary, while the rising group performed too conservatively in the 2-point loss session, the falling group performed too liberally in the 5-point session. These deviations appeared in the

Figure 27

The deviations from the optimal values $\gamma^*_{subj,phase}$



Note. The error bars are 95% highest density intervals (HDIs).

second session for each group, suggesting that the response criteria were not optimally adjusted between the first and second sessions.

3.4.3. Discussion

This study found that participants adjusted their response criteria based on changes in the size of the loss. However, as in Experiment 1, this adjustment is not optimal. When the optimal response criteria were extremely liberal or conservative, participants failed to adopt them. Notably, even when the environment was not penalized for clicking on the loss stimuli (i.e., there was no negative consequence of clicking on a loss stimulus), more than half of the participants did not use the optimal response criterion.

Drastic changes between sessions were observed in the final sessions for the rising group. The rising group adjusted their response criteria between the 0-point and 2-point loss sessions. In contrast, the falling group exhibited adjustment after the second session, specifically between the 2-point and 5-point loss sessions. These results suggest that the order in which the participants experienced the environment influenced their adjustment of the response criteria, although each group differed in when they made the adjustment. Notably, while the magnitude of change was consistent in both the rising and falling groups, the adjustment of response criteria was observed only in the falling group. This observation aligns with the concept of loss aversion, which posits that losses are given more weight than equivalent gains (Kahneman et al., 1991; Tversky & Kahneman, 1991). Consequently, the falling group can be regarded as adjusting their response criteria earlier compared to the rising group.

The results of the intermediate sessions with moderate losses indicated that the performance in these two sessions was influenced by the environment in which the participants first experienced them. When the participants first experienced an environment with large losses, the response criteria became more liberal later in the experiment when they encountered an environment with smaller 2-point losses. Conversely, when participants first experienced an environment without losses, the response criteria later became more conservative when they encountered an environment with larger 5-point losses. These findings suggest that prior experience influences subsequent performance and leads to suboptimal outcomes. Overall, the results of Experiment 2 suggest that although participants were able to adjust their response criteria based on changes in the size of the loss, the adjustment was not optimal, and prior experience could significantly impact performance.

3.5. Discussion: Study 2

Many types of decision-making can be understood as search. Previous studies indicated that patch-leaving decisions observed in sequential (Constantino & Daw, 2015; Garret & Daw, 2020; Hutchinson et al., 2008) and simultaneous (Fougnie et al., 2015; Wolfe, 2013) foraging tasks are related to a wide range of real-world decisions (Hills et al., 2015). However, a dearth of research has investigated diet-choice decisions using foraging tasks. Thus, we examined whether the search in the diet choice problem was optimal in an environment with uncertainty, using the signal-detection optimal diet model. We introduced a signal-detection optimal diet model that incorporates uncertainty in visual information during foraging. Our two experiments manipulated the model parameters and compared the participants' response criteria with the model prediction. In particular, we evaluated the participants' response criteria and their ability to adjust to changes in the environment. The results suggest that both the ratio of gain stimuli (Experiment 1) and the magnitude of loss (Experiment 2) influenced search strategies, but participants' behaviors were not optimal.

Of particular interest, participants adjusted their behavior in the diet-choice problem only between the third and last sessions, indicating that no adjustment occurred between the other sessions. Prior experience can influence search optimality and lead to deviations from the optimal strategies. Performance differed depending on the order in which the participants experienced changing environments, although both the rising and falling groups experienced the same environment. The distinct choice patterns observed in the rising and falling groups are consistent with previous research conducted on foraging in both birds (Getty & Krebs, 1985) and humans (Fougnie et al., 2015). Although these studies employed different tasks than our current study, the influence of the past environment remains evident. For instance, Fougnie et al. (2015) demonstrated in their patch-leaving problem that search duration in the visual foraging task was longer during falling phases compared to rising phases. These findings provide support for the notion that beliefs about the environment are updated during foraging and incorporate information from prior experiences (Wolfe, 2013; Zhang et al., 2017).

The necessity for inference is a critical aspect of our experiments. In order to perform the task in the current experiments without prior knowledge, participants had to infer the number of gain stimuli in the display. This inference was necessary because the colors representing the gain and loss stimuli overlapped, making it impossible for observers to determine with certainty whether a particular stimulus was a gain or loss stimulus. The inference process involved various forms of learning, including associative learning (Blaser et al., 2004; Cheng & Spetch, 2001), reinforcement learning

(Constantino & Daw, 2015; Kolling & Akam, 2017), and Bayesian updating (Bella-Fernández et al., 2021; Oaten, 1977). Specifically, in this particular case, Bayesian updating could contribute to suboptimal adaptation to each environment. Participants were not aware of the true ratio of gain stimuli (Experiment 1), resulting in an uncertain environment. This uncertainty may have caused participants to rely more heavily on past environmental experiences, leading to suboptimal adaptations. In other words, participants formed expectations about the current environment based on their experiences in the past environment. The mismatch between the expectation and the current environment leads to an inaccurate adjustment of the response criteria.

The mismatch can occur due to cognitive limitations and bounded rationality[4]. Bounded rationality refers to a form of rationality that takes into account the information accessible to decision-makers and their cognitive limitations (Simon, 1955). Decision-making is known to be rational within the constraints of limited resources (Bhui et al., 2021; Lieder & Griffiths, 2020). For instance, these constraints could involve suboptimal inference due to approximating the uncertain environment (Analytis et al., 2019; Beck et al., 2012). In the signal-detection diet choice model, accurate inference of the environment is crucial for setting the optimal response criterion (Equations 4 and 5). However, in the current experiments, participants needed to adapt their choices to an uncertain environment where the colors of the gain and loss stimuli overlapped. To make accurate inferences, participants needed to sample a sufficient number of stimuli, which was limited due to the restricted number of displays they could visit. This limited sampling may have resulted in a reliance on inaccurate inferences about the environment.

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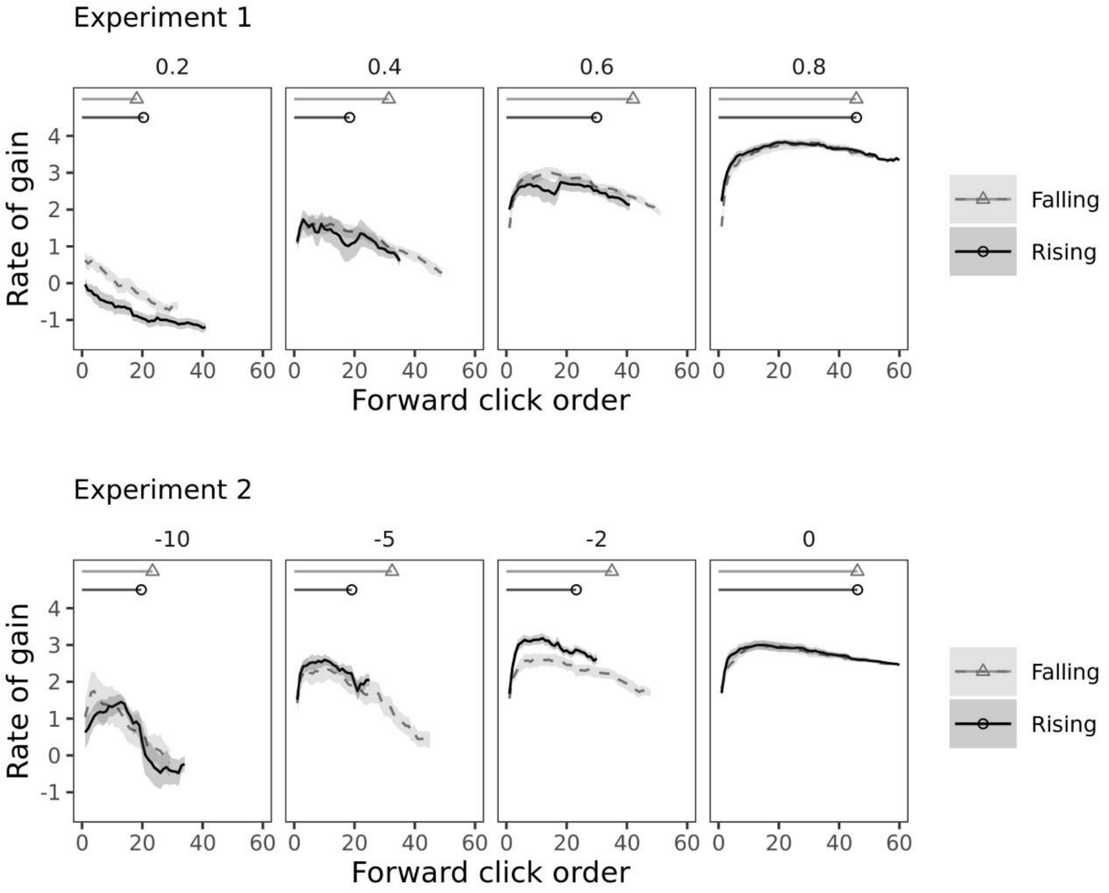
[4] We thank an anonymous reviewer for bringing this perspective to our attention.

Figure 28

Patch-leaving time and rate of gain in Experiments 1 and 2



Note. The curves represent the rate of gain within a display. The ribbons surrounding the curves indicate the standard errors. The triangles and circles depict the actual leaving times of the falling and rising groups, respectively.

Our findings have implications for decision-making research that uses foraging tasks, particularly for diet-choice problems. While previous studies have mainly focused on the patch-leaving problem, that diet-choice and patch-leaving problems share a common underlying principle: maximizing energy gain per unit time, as outlined by Charnov (1976a, 1976b). Our experiments also contained the patch-leaving component, requiring participants to decide when to conclude their search on each display. We computed both the rate of gain within a patch (as specified in Equation 3) and patch-leaving times (Figure 25). It is important to note that, however, our experiments were unable to ascertain the optimal patch-leaving time because the points acquired in the current display did not carry over to the next one. This limitation highlights the essence of the patch-leaving problem: it centers around decisions concerning missed opportunities. For instance, if foragers prolong their stay in the current patch, they risk losing potential gains in the subsequent display. To delve deeper into the relationships between optimal diet-choice and patch-leaving decisions, future studies could design experiments where points acquired in the current display do carry over to the next one. While these two decisions differ in nature and should not be conflated, they are interconnected components of the broader decision-making process in foraging tasks.

Another important aspect of our study is that the signal-detection optimal diet model allowed us to incorporate uncertainty into the theoretical analysis of search behavior. Surprisingly, experimental investigations have been limited to this topic, although the model was first introduced by Getty (1985). Our experimental setting provided a unique opportunity to examine his model's predictions in human visual foraging because it accommodates the uncertainty of decisions inherited by perceptual ambiguity. Indeed, the ability to discriminate between good and bad stimuli is significant in both animals (Sumner & Sumner, 2020) and humans. Combining this signal detection approach with foraging tasks might allow researchers to model several decision-making processes in perception and cognition as domain-general search processes (Hills et al., 2015; Todd et al., 2016).

The neural mechanisms underlying these behaviors have also been elucidated. Hayden et al. (2011) demonstrated that the anterior cingulate sulcus (ACC) plays a role in patch-leaving decisions in macaques, and Wittman et al. (2016) showed that the dorsal anterior cingulate cortex (dACC) is important for human patch-leaving decisions. However, the mechanisms involved in foraging behavior are yet to be understood due to a lack of neuroscientific investigations into the diet-choice problem. Our understanding of these complex behaviors could be improved through further research that utilizes both behavioral and neural approaches and focuses on the diet-choice and patch-leaving aspects of foraging.

Future studies should also address several unresolved questions. First, to improve the signal-detection optimal diet model, it is necessary to incorporate the effect of search history. Second, current experiments did not explore whether diet choice decisions could be optimal without environmental changes. Given that suboptimal choices were made in the first sessions of our study, it may be necessary to introduce additional assumptions and parameters into the diet-choice model to explain human foraging behavior. Understanding how observers solve diet-choice problems enables us to identify the cognitive constraints that contribute to the suboptimal behaviors observed in the current study. For example, conducting an experiment with a larger number of patches or longer time limits would be appropriate for further investigation of this matter. Third, future studies could combine diet-choice and patch-leaving problems by treating the choice of whether to search for a current patch or find another as a diet-choice problem. For example, when choosing between two fruit stands in a market, the decision can be based on a comparison of the appearance of fruits in the stands, contextual information, or previous shopping experiences. Finally, incorporating more complex stimuli or contexts in the task can provide a closer approximation to real-life search scenarios, which holds significance for future research. For instance, virtual environments have been employed to examine human foraging decisions (Wu et al., 2021). In these environments, observers' ability to process information is constrained by limitations in vision and attention. Exploring the impact of these constraints on foraging performance represents an important avenue for further investigation.

Although the present experiments used simple search displays, this task has the potential to be applied in more complicated or practical situations. Patch-leaving problems have been used to study perceptual search, reinforcement learning (Constantino & Daw, 2015; Kolling & Akam, 2017), search in memory (Hills et al., 2010), search for creativity (Hart et al., 2018), and social decision-making (Gabay & Apps, 2021). These decisions involve diet choices; incorporating both aspects of searches into decision-making studies expands our understanding of the search processes underlying various cognitive decisions.

In many decision-making processes, selecting the best option among multiple alternatives is difficult because the options usually have a degree of uncertainty. We investigated this situation using the diet-choice problem in foraging by combining modeling and behavioral experiments. In the experiments, the search performance deviated from the optimal value. Moreover, search performance was modulated as the environment changed across phases, although the adjustment was not optimal and was particularly affected by search history. Extending previous studies on human search and foraging, we show that expectations and learning play significant roles in diet choice problems. Foraging behaviors in nonhuman animals have been extensively studied in behavioral ecology, and recent neuroscientific studies have revealed a connection between animal and human decision making in foraging-type tasks. This line of research on foraging should prove useful in integrating animal and human decision-making into one framework. The current study provides a basis for further research in this area.

4. General Discussion

This thesis has developed an integrated framework based on the optimal foraging theory to examine visual information search in humans. The optimal foraging theory consists of two fundamental decision components. The first component is the patch-leaving decision, involving deciding when to leave the current environment and transition to a new one. Previous research in visual cognition and decision-making has utilized this problem to expand their investigative scope (Bella-Fernández et al., 2021; Constantino & Daw, 2015; Hall-McMaster et al., 2021; Hall-McMaster & Luyckx, 2019; Harhen & Bornstein, 2023; Hutchinson et al., 2008; Kolling & Akam, 2017; Kosovicheva et al., 2020; Kristjánsson et al., 2014, 2020; Wittmann et al., 2016; Wolfe, 2013; Wolfe et al., 2018, 2019). In contrast, the second component, the diet-choice problem, has been relatively overlooked.

The specific objective of this thesis is to investigate the diet-choice problem during visual foraging in humans. Study 1 demonstrated that the visual foraging task involves two types of decisions, and these two decisions were influenced differently by blocking feature learning. Particularly in Experiments 2 and 3, where each group of participants experienced an equal number of search displays, the effect of blocking was evident in the ratio of accurately clicking target stimuli. Participants subjected to the blocking manipulation were less accurate and less likely to click target stimuli compared to those without the blocking manipulation. In contrast, the effect of blocking was not observed in the patch-leaving decision. Participants in both groups consistently stayed longer than optimal in a patch, and the extent of the deviation did not differ depending on the blocking manipulation.

In Study 2, we examined the search strategies in the diet-choice problem during the visual foraging task. To incorporate uncertainty present in the task, we adopted the signal-detection optimal diet model and assessed the participants' decision criteria by estimating the parameters in the model with Bayesian hierarchical modeling. Additionally, we changed the search environment session by session to examine the effects of search history. We manipulated the number of target stimuli on a display in Experiment 1 and the magnitude of loss by blocking distractor stimuli in Experiment 2. Overall, participants adjusted the decision criteria as the environment changed. However, the adjustment was not optimal. In particular, the response patterns differed depending on the order of changes participants experienced, and the adjustment was overall delayed to the last session. These results show that the schedule of changes in the environment affects and deviates search performance from optimality, especially when the environment contains uncertainty.

4.1. Theoretical Insights

4.1.1. Visual Search

The visual foraging task has evolved from the visual search literature, which aims to examine the search for visual information in more realistic contexts. Visual information search in the real world is a complex activity. One way to tackle this complexity is to use experimental stimuli that are more complex than a set of simple shapes and letters. Visual search for an object in scene photos (Neider & Zelinsky, 2008; Võ & Henderson, 2011; Wolfe et al., 2011) and the theories developed from these studies (Henderson et al., 2009; Le-Hoa Võ & Wolfe, 2015; Tatler et al., 2017) are one example of this line of research.

Another way to approach real-world search is to make decisions involved in the task more complex. In the typical visual search task, which ends when a participant finds a target stimulus, an experimenter typically analyzes how long it takes to reach this decision and how accurate it is. The visual foraging task enables researchers to look into other metrics that have not been utilized. When a search display has multiple types of target stimuli (e.g., red and green stimuli), participants can switch between different target types during a foraging trial. The run pattern differed depending on the difficulty of the task: when stimuli are defined with basic visual features, the switch is more frequent than when stimuli are defined with the conjunction of features (Jóhannesson et al., 2017; Kristjánsson et al., 2014). In addition to the analysis of run pattern, Kristjánsson et al. (2019) list the rate of collecting target stimuli, the time that costs participants to switch target types, the slowing of a response on finding the last target stimulus in a display, the degree of organization of target-collecting behavior, and most importantly, patch-leaving time.

In this respect, the current studies introduced another way of analyzing visual foraging behavior. Previous studies on the run pattern have already pointed out the significance of analyzing the selection of stimuli in a patch. However, although the patch-leaving and diet-choice problems both comprise important components of the optimal foraging theory (Charnov, 1976a, 1976b; Stephens & Krebs, 1986), stimulus selection was not analyzed from this perspective. Study 1 established that these two types of decision are indeed involved in the foraging task, and they were influenced differently by the blocking procedure. Then, Study 2 showed a way to analyze this diet-choice behavior with behavioral experiments and modeling based on the optimal foraging theory.

Visual information search is a multifaceted activity, and observations from different perspectives are certainly needed to reveal how this search is conducted. The strength of using the visual foraging task also lies here because the task itself involves multiple decisions, and each decision can be considered and analyzed separately. In addition to the patch-leaving and diet-choice problems, Bella-Fernández et al. (2021) pointed out that the patch-learning problem, learning to select a better patch, also needs to be examined. Introducing the diet-choice problem contributes to the field by adding another viewpoint from which visual information search can be investigated.

4.1.2. Active Search

Moreover, this framework introduces a new perspective for studying human search for visual information. Previous research has focused on the cognitive mechanisms within the visual search task and the neural architecture behind them. As seen in studies reviewed in this thesis and elsewhere (Eckstein, 2011; Wolfe, 2014, 2020), it has offered numerous significant insights into how visual processing works during the visual search task. The theories presented in the visual search literature correspond to the 'mechanism' question in Tinbergen’s four questions (Table 1). In other words, previous studies have revealed how finding a target stimulus is achieved in the visual search task.

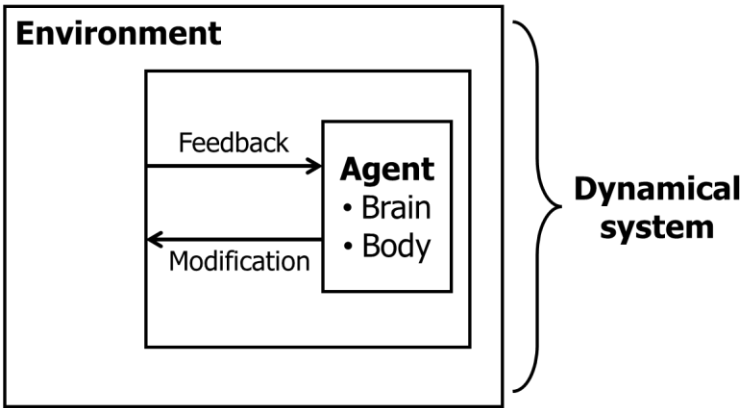
The framework based on the optimal foraging theory, by contrast, addresses the 'function' question. Specifically, the optimal foraging theory consists of three main components: choice, currency, and constraints (Stephens & Krebs, 1986). The choice assumption pertains to the type of decisions agents make, often expressed as variables in an algebraic model. In the context of the diet-choice problem, this assumption involves the decision of whether to consume the currently encountered food. In the current signal-detection optimal diet model, this corresponds to the probability of choosing a gain stimulus, denoted as ϕ.

The currency assumption specifies the criterion for evaluating the value of the decision variables. It can take various forms depending on the tasks and animals involved in an experiment, such as the caloric intake per time for honeybees feeding on flowers (Waddington & Holden, 1979) or the number of pelts consumed by birds (Erichsen et al., 1980; Houston et al., 1980). In the experiments in Study 2, it was the optimal search efficiency (R^*), simulated in Figure 16.

The constraint assumption defines the factors that limit the interaction between the choice and currency assumptions. For example, in the current experiments, participants did not determine the number of gain and loss stimuli on a screen or the amount of points acquired by clicking a stimulus. More importantly, the model assumed that the agent only has partly complete information: the type of stimulus, whether gain or loss, cannot be perfectly recognized based on color due to the overlapping colors of gain and loss stimuli. These constraints define the choices available to agents, as well as how to maximize the currency.

Figure 29

Schematic representation of the dynamical approach



Note. The figure is adopted and modified from Beer (1995).

With these assumptions, the approach based on the optimal foraging theory can assess the interactions of the environment and the agent as a dynamical system (Figure 29). The agent searches for a target stimulus in the environment, modifies the environment by choosing a stimulus that disappears after the choice, and receives feedback in the form of points in the current experiments. This interaction is expressed through the currency assumption, which defines search efficiency as the rate of point acquisition per unit of time (Equations 14 and 15). Rather than examining what is happening inside the agent, the current approach deals with the system of this interaction as a whole.

In other words, the search for visual information can be considered as temporally extended patterns of behavior (Rachlin, 1992, 2013, 2017). To understand behavior in terms of its function, it is necessary to view the behavior in the context of an extended period of time. The motive of a thief cannot be understood merely by observing the moment when the person is picking up a product; instead, observing the entire sequence of actions reveals their motives for stealing the product. Similarly, understanding the search for visual information as a behavior requires observing it over a course of time. The visual foraging task is one example that serves this purpose because it does not conclude in a single trial; rather, it spans multiple trials in which participants are allowed to explore and interact with the environment.

4.2. Future Directions: Integration with Decision-Making Research

4.2.1. Reinforcement Learning

Using the framework based on the optimal foraging theory, the research on visual information search has the potential to expand its horizons and integrate with other areas that also utilize a similar framework. In a natural setting, a vast number of alternatives are presented, and decision-makers must observe the rewards corresponding to each option by exploring the environment. Options can be buttons to peck in operant conditioning (Baum, 1974; Herrnstein, 1961) or arms to choose in the multi-armed bandit problem (Speekenbrink & Konstantinidis, 2015; Steyvers et al., 2009; Sutton & Barto, 2018). The reinforcement learning literature also began to use a type of foraging task to investigate choice behavior when choosing among multiple alternatives with different values. This type of foraging task is called the sequential foraging task because each alternative is presented serially. The task is based on the multi-armed bandit task, which has been extensively studied in the reinforcement learning literature in decision-making research.

In the multi-armed bandit problem, the environment consists of a set of options and corresponding outcomes. For example, two colored rectangles (e.g., yellow and blue) are presented on the screen, and participants' task is to choose either of the rectangles. A choice typically results either in monetary reward or loss. The choice of a yellow rectangle leads to reward in 70% of the trials, while the choice of a blue rectangle leads to reward in 30% of the trials. In either case, decision-makers do not have the information about which option corresponds to reward or punishment. In order to understand the structure of the environment, they need to sample the reward rules from the environment through trial and error. In other words, this exploration involves the process of searching among options in the environment.

Extensive research on the multi-armed bandit problem has focused on understanding the learning process related to the value of each option. In the k-armed bandit problem, each of the k options is associated with an expected reward if the option is selected. The expected reward for selecting an option is referred to as the 'value' of that option and is defined as follows: We denote the action of selecting an arbitrary option as A, the value of that action at time step t as a and the reward corresponding to that action as R_t.

$$q_*(a) = \mathbb{E}[R_t|A_t = a]$$

(19)

If decision-makers have complete knowledge of the value of each action (a), selecting the best option is a straightforward task. They simply choose the option with the highest value. However, in most cases, decision-makers lack this information, which necessitates exploration for a better option. They must estimate the expected value of action A by exploring various options and updating their estimates to be as close as possible to $q_*(a)$.

However, most decision-making in our life is more complicated than the situation in the multi-armed bandit task. One of the complexities in decision-making in a natural setting is the volatility of the environment. For example, the environment can change in the course of actions. The typical multi-armed bandit task is usually set in a stable environment, where the expected reward of arms is unchanged. Speekenbrink & Konstantinidis (2015) conducted an experiment with a 'restless' bandit task, where the expected reward of each arm changed over time. In their experiment, the reward of each arm was sampled from a normal distribution. The mean of the normal distribution varied during the experiment following the random walk. The result showed that participants explored more by switching between arms when the environment was more volatile. This finding suggests that the search in the environment contributes to decreasing the uncertainty of the environment.

Another complexity in real-world decision-making involves dealing with a vast number of possible actions. Wu et al. (2018) conducted a study using a 121-armed bandit task to explore decision-making in a complex environment with a multitude of potential actions. In such scenarios, it becomes impractical to evaluate and learn the reward rules for every option due to limitations in resources and time. To investigate how individuals navigate such an expansive problem space, the researchers introduced a spatial correlation within the environment. For example, among the 121 options, they positioned reward-associated arms in close proximity. Their findings indicated that decision-makers acquire an understanding of the environment's spatial structure and use it to make generalized decisions within the extensive problem space. In a subsequent study by Wu et al. (2020), they further demonstrated that the generalization based on exploration was applicable not only in spatial tasks but also in non-spatial tasks.

4.2.1.1. Sequential Foraging

Not only is the environment, but also the decision involved in a naturalistic setting more complicated than that studied with the multi-armed bandit task. A number of recent studies have focused on the patch-leaving decision as another choice people make in daily life. This line of research employs a sequential foraging task, which is more similar to the multi-armed bandit task rather than the visual search task. For example, in Hutchinson et al. (2008), participants played a fishing game where a fish occasionally appeared on the screen. Participants tried to catch as many fish as possible by the end of the experiment, achieved by clicking on a fish with the mouse. The rate at which fish appeared decayed over the course of the experiment, and participants could switch ponds whenever they chose to move to a new environment. In essence, they needed to address the patch-leaving problem to maximize the number of fish they caught by the end of the experiment.

These studies primarily analyze how values assigned to each option are updated and how the environment influences choices in the sequential foraging task. Wittman et al. (2016) demonstrated that humans tracked a gradual change in the sequential foraging task. Furthermore, they utilized the reinforcement learning algorithm to illustrate that participants tracked the environment by comparing past and recent rewards, with this comparison linked to the dorsal anterior cingulate cortex (dACC).

Constantino & Daw (2015) integrated the marginal value theorem of the optimal foraging theory with the reinforcement learning algorithm to investigate how participants adapt their behaviors in response to environmental changes. They found that trial-by-trial choices can be explained by the MVT-based value updating rule.

These studies demonstrated the utility of the foraging approach in the reinforcement learning literature by emphasizing two key points. First, this approach broadens the range of situations addressed by decision-making literature. The crucial feature of the foraging approach is that decision-makers need to learn not only about the current environment but also about the background environment they are not actively exploring. This type of decision-making is relevant not only for maximizing rewards in sequential decision-making scenarios (Hall-McMaster et al., 2021; Kolling & Akam, 2017) but also for a wider array of decisions, including mate selection and economic choice (Frankenhuis et al., 2019; McCall, 1970; Pearson et al., 2014).

Second, it establishes a clear connection with cognitive neuroscience. Research with non-human primates has suggested the role of dACC in tracking the threshold for the patch-leaving decision (Blanchard & Hayden, 2014; Hayden et al., 2011). Research with humans has also indicated that the anterior cingulate cortex (ACC) encodes the richness of long-term foraging environments (Kolling et al., 2012; Rushworth et al., 2012). This role of the ACC contrasts with that of the ventromedial prefrontal cortex (vmPFC), which tracks the relative value of the current option compared to another option (Boorman et al., 2009; Noonan et al., 2011; Rushworth et al., 2012). These findings expand the scope of decision-making research by suggesting that two distinct and independent types of decision-making, one for the current decision and one for foraging, are at work in the frontal cortex.

4.2.2. Integration

The current studies have provided insight into the integrated framework of visual information search. Despite differences in tasks, common themes emerge, including the uncertainty and partial observability of the environment, the variety of possible actions, and the distinction between the patch-leaving and diet-choice decisions. To integrate the current framework with sequential foraging, further studies are needed to examine why the deviation from optimality is consistently observed. Overstaying in the patch-leaving problem has been reported in both animal (Hayden et al., 2011; Kane et al., 2019) and human foraging studies (Hutchinson et al., 2008; Wolfe, 2013; Wolfe et al., 2018, 2019). Additionally, as shown in our Study 2 and others in the animal foraging literature, diet choice also deviates from the optimal decision.

Harhen & Bornstein (2023) provided an example where additional assumptions of the model supported the optimal strategy instead of refuting it. Recently, they demonstrated that overstaying may result from an adaptive strategy. Participants visited different planets to unearth 'space treasure.' In each trial, they landed on a planet, conducted a treasure dig, and faced a decision: whether to remain on the current planet or shift to a new one. The longer they stayed on a planet, the more the returns on the treasure diminished after each dig. Moving to a new planet restored the potential treasure yield, but it consumed time that could otherwise be used for additional digs. The results suggested that participants tended to overstay on a planet when the decay rate of the returns was slow or intermediate. Computational modeling revealed that this overstaying was not due to suboptimal decision-making. Instead, it reflected that participants' decisions may be based on discounting the prediction of the subsequent decay rate, and this decay rate was estimated based on knowledge about the uncertainty in the environment.

Thus, overstaying in the task may result from learning about the environment and adapting to it. Whether the consistently observed overstaying in Study 1 and the deviation from optimality in Study 2 are also results of similar adaptation is a topic that awaits further discussion. The task used in the current studies presents stimuli in one patch simultaneously, which differs from the assumption in the sequential foraging task. To apply a variety of computational models from the reinforcement learning literature (Sutton & Barto, 2018), participants in the visual foraging task can use information about one or two items ahead of the target stimulus they are currently engaging with (Kosovicheva et al., 2020). Research on eye movements during reading has utilized the gaze-contingent technique, where only fixated information is presented to participants, and non-fixated information is occluded (McConkie & Rayner, 1975; Rayner, 1975). Using this technique in the visual foraging task involves presenting visual stimuli serially while maintaining the component of searching for visual information inherent in the task.

4.2.3. Importance of Understanding Cognitive Search as Foraging

By integrating research on decision-making and visual information search, it becomes possible to construct a research program that treats search in a broader context. This approach allows researchers to consider the search for visual information in physical space and the search for information in problem space under one overarching framework. It provides valuable insights into investigating two prevalent decisions in search: determining what to search for within the current display and deciding when to transition to the next display for further search. For instance, searching for ripe berries in a field of bushes (Wolfe, 2013) serves as an example that involves both of these decisions. Moreover, these two types of decisions may play important roles in a variety of activities, spanning from perception to creative thinking (Hills et al., 2015; Todd et al., 2016).

Search is necessary for visual perception because only visual stimuli falling on the foveal region of the retina receive high-acuity processing. The central fovea covers an area of only about 2 degrees of visual angle, and acuity and contrast sensitivity rapidly decline as the distance from the center of the fovea increases (Levi et al., 1985; Rovamo et al., 1984). To perceive visual scenes that spread more than 2 degrees, eye movements to various regions of the scene are necessary. Generally, determining where to look next in the visual scene is influenced by bottom-up saliency or top-down knowledge (Henderson, 2007). Saccades, which are rapid eye movements, are attracted to visually salient regions of the scene (Foulsham & Underwood, 2008; Itti & Koch, 2001; Koch & Ullman, 1985). Simultaneously, the goal of the current task or the semantic knowledge of the scene guides eye movements (Tatler et al., 2011; Torralba et al., 2006).

Furthermore, when searching for information on the internet, it is common to leave the current webpage and navigate to the next one (Pirolli & Card, 1999). Recent studies have also highlighted the presence of these types of searches in cognitive domains such as working memory (Hills & Pachur, 2012) and semantic memory (Hills et al., 2012; Wilke et al., 2019). The decisions entailed in the foraging task extend beyond perceptual search and encompass a range of decisions encountered in everyday decision-making, including creative thinking (Hart et al., 2017, 2018, 2022) and social decisions (Gabay & Apps, 2021; Turrin et al., 2017).

Although most of these studies have treated the processes involved as search, the assumed mechanism is closer to reinforcement learning than search. As pointed out by Hills et al. (2015), these processes share the same exploration-exploitation dilemma. In the search in working memory, for example, the search strategy switched between a local focus and a global focus: the local focus is based on the similarity between memory items, and the global focus is based on the frequency of the item's appearance (Hills & Pachur, 2012). Similarly, in a task where people created a unique shape with ten connected squares, they switched between the exploration and exploitation phases (Hart et al., 2017). They created related shapes belonging to a certain category (exploitation) and then moved to a new category (exploration). This approach has focused on the process that unfolds over the course of multiple searches—the alteration of the exploitation and exploration phases—rather than the process that unfolds within a single search.

In order to understand what is happening within the search, it is significant to acknowledge that search is a temporally extended behavior. Merely observing the result of the search, typically expressed as reaction time or accuracy, does not allow us to examine the extended patterns during the search. On the other hand, as mentioned earlier (4.1.2. Active Search), the framework based on optimal foraging theory may allow us to understand search as a whole, as a dynamic system between the agent and the environment. Applying this approach to cognitive search is not an easy task because defining the search environment is not as straightforward as in the visual foraging task. However, future studies in this line would make it possible to define various 'searches' as temporally extended patterns of behavior, thus allowing a deeper understanding of the search itself.

By doing this, another avenue to integrate two branches of the studies of the mind—philosophy and psychology—emerges. Following in the footsteps of phenomenologists, the enactive approach to cognition suggests that the mind is the activity through which interaction of an agent with the world brings forth a meaningful world (Gallagher, 2017, 2023). Based on this approach, Chemero (2011) proposed explaining the behavior of the agent as a coupled dynamical system described by a difference equation evolving over time. Foraging is the activity where animals interact with the environment throughout feeding activities. These two entities are coupled in the way that they cannot exist without one another. Similarly, human cognition may be an activity that emerges from the pattern of interaction between the agent and environment (Thompson & Varela, 2001; Varela et al., 1993). This should be a productive avenue for future studies.

5. Conclusion

The aim of the thesis was to gain a better understanding of the search for visual information by applying the framework based on optimal foraging theory. The experiments in Study 1 confirmed that there are indeed two types of decisions involved in the visual foraging task: the patch-leaving and diet-choice problems. In Study 2, the signal-detection optimal diet model was employed to predict behavior during the visual foraging task in terms of the uncertainty in the environment. The relevance of prior experience in the environment is strongly supported by the current findings. This project represents the first comprehensive investigation of the diet-choice problem within the visual foraging task in an experimental setting. While the scope of this study was limited to situations in the visual foraging task, its findings can be generalized to include decision-making and cognitive search. Further research with this approach not only allows us to understand a broad range of cognitive processes as search but also encourages us to think about the mind in a new light, as temporally extended patterns of behaviors.

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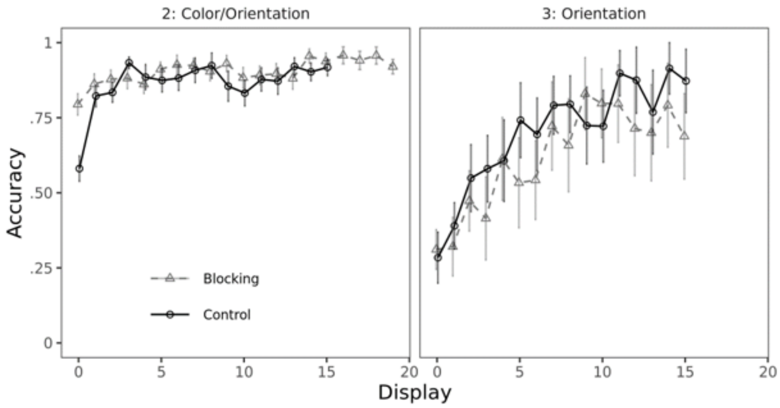
Appendix 1

Accuracy of Target Clicking in Each Display

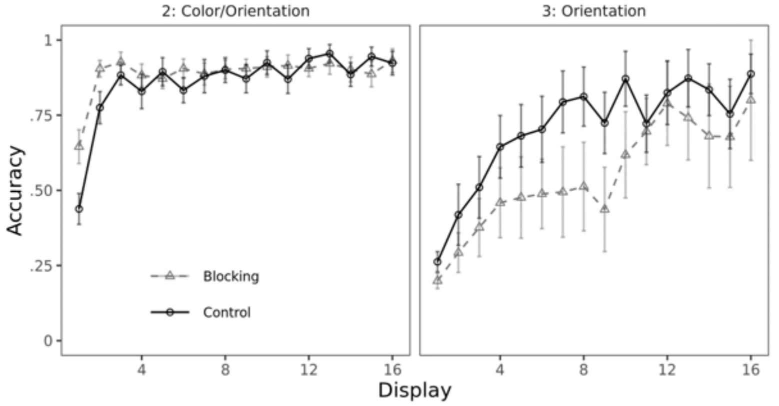
(a)

Experiment 1



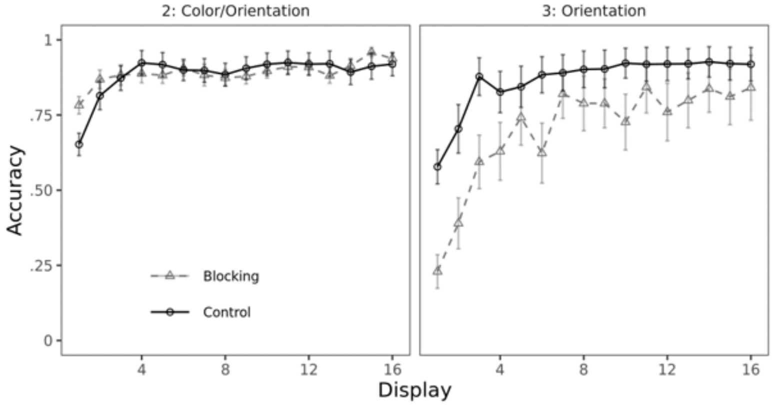
(b)

Experiment 2



(c)

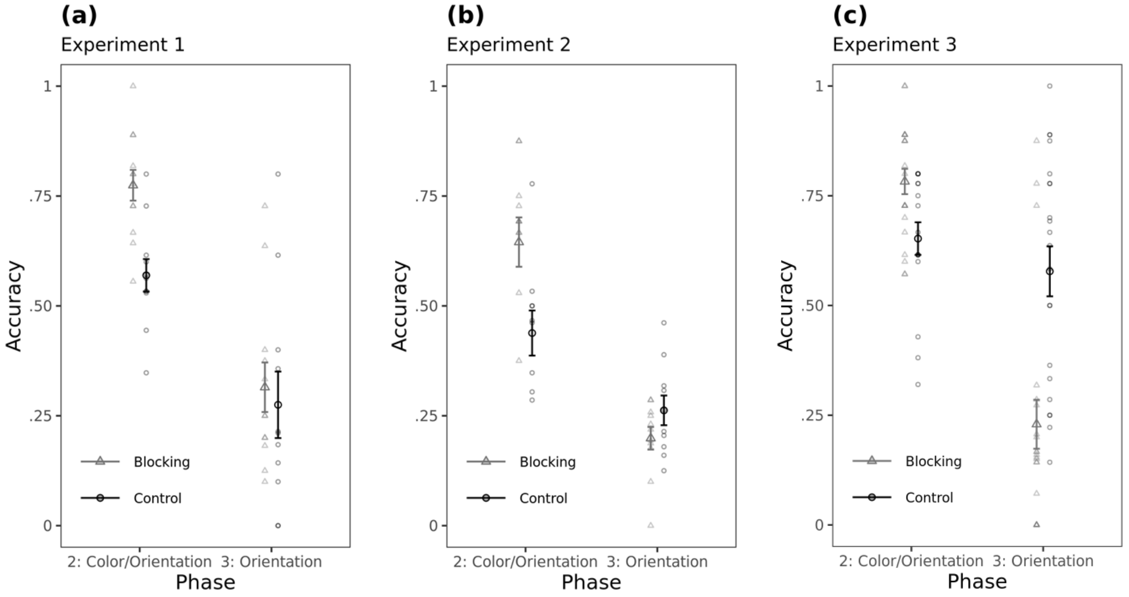
Experiment 3



Note: Each panel corresponds to the Color/Orientation and Orientation sessions. The error bars represented standard errors.

Appendix 2

Accuracy of Target Clicking in the Initial Display of Each Phase



Note: Error bars indicate standard errors. Transparent markers represent the mean accuracy of each participant.

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